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Improving Classification Efficiency by Restructuring Army Job Families

Cecil D. Johnson, Joseph Zeidner, and Julia A. Leaman
The George Washington University

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This report presents one of a series of studies designed to improve classification efficiency by applying principles of differential assignment theory. The major objectives of this study are to examine classification efficiency as a function of the number of job families and to examine alternative methods for clustering or forming job families. Factors investigated include alternative methods for constructing assignment variables or predictor composites; the effects of using a more economic criterion, size, and heterogeneity of the test battery from which assignment variables are formed; and the size of analysis samples used to form assignment variables.

Sets of synthetic scores (entities) that have the statistical properties of empirical test scores were generated. The synthetic entities were assigned under the differing experimental conditions being simulated, and mean predicted performance was computed for each alternative being investigated to form the unit of comparison among alternatives. We refer to the simulation of personnel systems process using synthetic scores as model sampling. A cross validation design was employed that

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eliminated traditional back sample inflation due to sampling error. In one design, 18 jobs from Project A, validated against core technical proficiency criteria, were used in a model sampling experiment. In a second design, 60 jobs were used validated against skill qualification tests.

In the 18-job case, the use of full least square (FLS) composites of the 29 Project A predictor variables (9 ASVAB tests and 20 experimental tests) for making optimal assignments to 12 classification-efficient composites provides an increase of 299 percent over the operational aptitude areas and their associated 9 job families. In the 60-job case, changing from FLS-ASVAB composites and their associated 9 operational job families to FLS-ASVAB composites and a classification-efficient set of 23 job families provides a gain of 177 percent. Findings also show that the use of the FLS assignment variables alone derived from the present ASVAB provides a 133 percent improvement over the use of operational aptitude areas as assignment variables. In contrast, the additional classification efficiency provided by adding all 20 of the Project A experimental variables to form a new, much larger classification battery is a further average gain of 29.1 percent in mean predicted performance in the 18-job case.

This study presents further evidence strongly supporting the principles of differential assignment theory and suggests a number of operational steps that should be implemented to permit effective personnel classification.

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Improving Classification Efficiency by Restructuring Army Job Families

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FOREWORD

This report is one of a series of research efforts designed to improve the selection and classification efficiency of the Armed Services Vocational Aptitude Battery (ASVAB). The research reported is unique in that it contributes to both methodological issues in personnel assignment theory and to the formulation of new job-matching policies based on scientific principles. It is an example of how basic research can stimulate and provide direction to applied research.

Two important general conclusions can be drawn from the findings. First, we see a higher classification efficiency inherent in the ASVAB than is usually posited. Second, the existing operational assignment composites could be reconstituted to substantially improve classification efficiency by considering the expansion of the number of job families, by clustering jobs into classification-efficient job families, and by using assignment variables of least squares estimates of performance based on all variables in the operational test battery.

Such a major reconstitution of job families in the Army's classification systems must be based on all available validity data as well as on information available from job analyses. A number of personnel classification and assignment policy issues also must be resolved before a new system incorporating differential assignment concepts and principles can be implemented. The results of this research, however, should eventually lead to very substantial gains in classification efficiency.

EDGAR M. JOHNSON
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IMPROVING CLASSIFICATION EFFICIENCY BY RESTRUCTURING ARMY JOB FAMILIES

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SUMMARY

A. Introduction

The present selection and assignment model sampling experiment is a basic research effort that contributes to the practical body of knowledge essential to both a formulation of personnel job matching policies based on scientific principles and the design of research to provide effective techniques and tools for the implementation of these policies. The findings of this experiment are organized and interpreted in the context of differential assignment theory (DAT).

Our knowledge of DAT derives from the results provided by psychometric theory, modeling, and simulations of personnel selection and classification processes across a broad area of topics that includes specifying and evaluating (1) personnel measures for inclusion in experimental and operational batteries; (2) selection and assignment variables such as aptitude areas (AAs); (3) selection and assignment strategies and algorithms; and (4) sets of job families corresponding to the assignment variables. This study focuses on the latter, more specifically, on the gains in mean predicted performance (MPP) obtainable from a reconstitution of Army jobs into more numerous and more classification-efficient sets of job families for use in the classification process. As a result of the findings of this study DAT is extended and refined, and the immediate operational implications for the Army classification system become evident.

In this summary, we emphasize the practical findings derived from the model sampling experiment described more completely in the body of the report. As noted, the results of this study have immediate implications for policy makers. When these results are considered in the broader context of DAT, they point the way for immediately effecting major improvements in the personnel classification system and a longer range redesign of the personnel classification system to maximize classification efficiency. This complete redesign should not be completed

until further validity data becomes available. Expected results have the potential of improving the Army's annual productivity by an amount that would cost the Army hundreds of millions of dollars each year if achieved by using alternative approaches such as recruiting a greater proportion of high-quality personnel or the use of longer and/or more intense training programs.

B. Operational Issues

For more than a decade, there have been a number of advocates calling for the reduction of the number of job families used by the Army in its classification system. These advocates frequently pointed out that there are no more than four strong content clusters (i.e., group factors) in the test content of the ASVAB and that four job families corresponding to the Air Force's four job groupings would adequately reflect ASVAB content. Such an argument, of course, requires the equating of predictor dimensionality with the number of job families to which these predictors can be used to make reliable assignments. Proving this argument to be fallacious is a major objective of this study.

We argue that mean predicted performance (MPP) is the figure of merit most appropriate for comparing the benefits obtainable from the implementation of alternative system designs and operational strategies for selecting and assigning personnel. Unfortunately, many investigators prefer to use predictive validity as the measure of classification efficiency. They define classification efficiency in terms of the effect that proposed changes have on the validities of assignment variables for performance in jobs within their associated job families.

Investigators that rely on predictive validity as the measure of classification efficiency are typically quite pessimistic about the value or utility of personnel classification. They appear to be greatly influenced by the degree of unidimensionality in the predictor space and the undeniably dominant contribution that the largest principal component (PC) factor makes to both the predictor intercorrelations and validities. Thus, they assert that the dominance of the first (largest) PC factor prevents the realization of significant classification effects. These advocates also are typically impressed with the lack of stability in regression weights when used in independent samples. Much of this pessimism results directly from the use of predictive validity as the measure of classification efficiency.

The present research uses MPP as the measure of classification efficiency and permits effects of both dimensionality and instability of regression weights to appropriately affect measures of classification efficiency. The results remain entirely free of the effect of all sample error and biases in one experiment (Design A) and are essentially free of all biases that might affect the comparisons of the primary conditions in the second experiment (Design B). A cross validation design is used in both.

Factors relevant to the design of an optimal classification component of personnel systems are investigated in this study. These factors can be summarized as follows:

1. Number of job families and corresponding assignment variables, (e.g., the Air Force has 4 composites or assignment variables, the Army has 9, the Navy has 11 and the Marines have 5). DAT recommends as many as can be provided stable weights for the assignment variables (AVs) by the available validity data.
2. Alternative methods for forming job families.
3. Alternative methods for constituting AVs.
4. The effect of using a more economical criterion variable, (e.g., use of the Skill Qualifications Test, SQT, to determine job family structure and its use as the dependent variable for computing "best" weights for the formulation of assignment variables).
5. Size and heterogeneity of the test battery from which the assignment variables are formed.
6. Size of analysis samples required to form assignment variables, (e.g., by computing "best' weights for the tests in a test composite).

In the present study, emphasis is on the first two of the six factors outlined above. The remaining four factors are introduced, in a less complete fashion, to provide a contextual basis of determining practical interactions with the two primary factors. Mean predicted performance (MPP) is used to compare levels within and across these factors.

C. Research Approach

It is possible to conduct a study of this type either by drawing samples from a large data bank of empirical test scores or by generating sets of synthetic scores which have the statistical properties of empirical scores, including their expected intercorrelations, validities, means, variances, and shape of their score distributions. In either case, the assignment and classification processes associated with each alternative policy being investigated must be simulated and mean predicted performance computed at the conclusion of each simulation.

We chose to conduct the present study by generating sets (vectors) of synthetic scores separately based on the data from multiple jobs, 18 and 60 respectively, provided by two major Project A empirical studies. Each empirical data set is corrected for restriction in range due to selection effects and the criterion variables corrected for unreliability. The corrected predictor covariances and validities are then used to represent the two separate designated populations from which synthetic scores are drawn. The Design A experiment uses Project A concurrent study data which provides the covariances of 29 predictors and validities for 18 MOS provides. These 18 empirical samples provide the parameters to define the designated population for Design A.

Covariances among ASVAB tests and validities of these tests against SQT scores for 60 MOS were selected from a Project A data bank, corrected for restriction in range and attenuation, and used to compute the parameters to define the designated population for Design B. Both designated populations are assumed to represent the same youth population.

We refer to the simulation of personnel system processes using synthetic scores as model sampling. Our use of model sampling has several major advantages over the use of empirical scores to conduct system simulations. For example, model sampling permits the generation of as many independent samples as desired from the population from which recruiting and selection is accomplished, and thus allows the use of a research design that controls or measures the effects of different sources of sampling error or bias.

In Design A, the designated population is used to generate: (1) an analysis sample with the same number of entities in each MOS as is present in the empirical data set used to define the designated population, and (2) 20 independent cross samples for use in the simulations. Each

cross sample is used separately for each condition in a repeated measures design. The analysis sample is used in applying the empirical job clustering method to form job families and in computing the "best" weights to be applied to cross sample scores to form predicted performance measures (FLS composites) for use as AVs in the simulations. Weights from the designated population are applied to cross sample scores at the completion of each simulation to obtain the MPP standard scores used as measures of classification efficiency.

The designated population of Design B serves as the source of weights for both assignment and evaluation variables. The assignment variables represent predicted performance within job families while the evaluation variables are the predicted performance measures separately computed for each job. After optimal assignment to a job family each entity is randomly assigned to a job within that family and the entity's predicted performance score computed. While scores for all evaluation variables are computed using weights computed on independent samples, avoiding traditional back sample inflation, the less well known effect of correlated error across assignment and evaluation variables was not eliminated in Design B as it was in Design A. Since psychometricians lack experience in the effects of this kind of bias, we avoid making the kind of *experimental comparisons* in Design B which would be most affected by its presence. We do not, for example, contrast the classification efficiency of a priori and empirically determined weights for the test composites making up the assignment variables of Design B.

D. Major Findings

1. Design A

It is unfortunate that in this experiment, for Design A, we have the best criterion variables, but we also have only 18 jobs. This limitation severely limits what we can determine in this experiment and is the reason why we also provided for Design B where 60 MOS could be utilized. However, some of the most important conclusions of this study are drawn from Design A where we have both the more credible criterion variables and a more complete control of correlated error and biases.

In each simulation of both Design A and Design B, we first reject 25 percent of the entities of each sample on the basis of their AFQT scores. We then optimally assign the entities to job families. All MPP standard scores reported in this summary give the expected MPP standard score after the results of selection were subtracted from the total MPP standard score obtained as a result of simulating both selection and optimal assignment. For our baseline condition in Design A, we distribute the 18 jobs into the current 9 operational job families and use the existing aptitude area (AA) scores as the assignment variables.

Making selection and assignment decisions by chance yields an MPP standard score equal to zero. Selecting 75 percent of the entities as having the highest AFQT scores, provides an expected MPP of .225 for Design A under the hypothetical condition of random assignment to jobs. Using the operational AAs and job families in conjunction with an optimal assignment algorithm adds only .092 to the MPP standard score. As noted above, we use this condition in Design A as our baseline against which to examine the gains obtainable from adding improvements by stages; the percentage improvement over both the baseline condition and the previous stage is given at each stage.

In stage one, we *substitute* 9 *least square weighted* composites based on the full ASVAB (FLS-ASVAB composites) for the 9 operational aptitude area composites. This yields an MPP attributable to classification effects of .214, an increase over baseline of 133 percent.

In stage two, we substitute the 9 classification-efficient job families for the 9 operational job families while using the corresponding FLS-ASVAB composites as assignment variables. This provides an MPP that is greater than that provided by selection (MPP = .245), a percentage increase over baseline of 166 percent, and a gain over stage one of 14.5 percent.

For stage three, we increase the job families from 9 to 12 while still using corresponding FLS-ASVAB composites as assignment variables. This change provides an MPP due to classification of .277, an increase of 201 percent over baseline and 13 percent over stage two.

Stage four involves the substitution of the 29 Project A concurrent validation experimental variables for the 9 ASVAB tests in the computation of the corresponding FLS composites -- providing a measure of the upper limit of the gain in MPP obtainable from the optimal use of the Project A experimental predictors to expand the dimensionality of the operational classification battery. The use of these FLS-experimental composites for making

optimal assignments to the 12 classification-efficient job families provides an MPP due to classification of .367, an increase of 299 percent over baseline and 32.5 percent over the MPP obtained in stage three.

The reduction in the number of job families from 9 to 6 provides a reduction in MPP to .191 when the FLS-ASVAB are used as AVs; this is a 22 percent reduction when compared to the stage two results. A reduction of 24 percent results if FLS-experimental composites are used instead of FLS-ASVAB composites in a parallel comparison of assignment to 6 classification-efficient job families as compared to the use of 9 classification-efficient job families for this purpose.

2. Design B

The 60 MOS for which Skill Qualification Test (SQT) scores are available permit the clustering of jobs into three sets of a priori job families as follows: (1) the 9 operational job families used by the Army for initial classification and assignment; (2) 23 of the Army's 35 career management fields (CMFs); (3) an intermediate set of 16 families based on a compromise between the two sets of a priori clustering concepts. An empirical classification-efficient clustering algorithm was used to provide parallel sets of 9, 16 and 23 job families. MPP is computed after all of the entities are optimally assigned to a job family within one of the six sets of job families. The FLS-ASVAB composites are used as assignment variables for making optimal assignments to job families within each of the six sets.

The Design B baseline is provided by FLS-ASVAB composites using the 60 jobs formed into the 9 operational job families. This results in an MPP standard score of .135. The use of 16 a priori job families results in an MPP of .258, a 91 percent improvement. An increase to 23 CMF job families results in an MPP of .297, an improvement of 120 percent. Similarly, increasing the number of empirically determined classification-efficient job families from 9 to 16 improves MPP by 24.4 percent, and an increase from 9 to 23 job families in the classification system provides an improvement of 40.6 percent. The above results, plus those obtained from an increase from 16 to 23 job families, are provided in Table S-1.

The substitution of the empirically determined job families for the a priori job families increases MPP by 97 percent when there are 9 job families, 28 percent when there are 16 job families, and 26 percent when there are 23 job families. The total gain in MPP achieved from

Table S-1

COMPARISON OF DIFFERENCES AND PERCENTAGE GAINS IN MPP USING SQT AS THE CRITERION FOR 60 JOBS

Number of Job Families

	Empirical		Operational	
Increase from:	Difference	% Gain	Difference	% Gain
9 to 16	.065	24.4	.123	91.1
16 to 23	.043	13.0	.039	15.1
9 to 23	.108	40.6	.162	120.0

changing the structure of the 60 MOS from 9 operational job families to a classification-efficient set of 23 job families provides a gain of 177 percent, of which 120 percent is immediately obtainable from the increase in number of job families and the additional 57 percent can then be obtained from also using the improved method of structuring jobs. If the first change is in the method of forming job families, the first gain is 97 percent and the second gain, from also increasing job families from 9 to 23, is 80 percent.

E. Conclusions and Recommendations

1. Theoretical Implications

The findings of this study strongly support a number of DAT principles including:

a. The largest immediate improvement that can be provided for any personnel classification system is the use as assignment variables of least square estimates of performance based on all variables in the operational test battery, that is, the adoption of full least square (FLS) composites as replacements for the present type of aptitude area composites.

b. The optimal number of job *families for inclusion* in an FLS composite based personnel classification system is as many families as can be coupled with adequately valid assignment variables. The factor limiting the number of job families is the availability of validity data for the constituent jobs in the job families. For example, although there are approximately 260 entry-level Army jobs, the Project A database used for this study would not be able to provide even minimal validity data for more than about 40 job families.

c. Whenever it is not feasible to provide separate FLS composites for each job, it is essential that jobs be clustered into job families in a manner that maximizes classification efficiency.

d. The expansion of the dimensionality of the classification battery by the inclusion of more predictors with greater heterogeneity can be expected to increase the potential classification efficiency to about the same extent as can be accomplished by the use of more classification-efficient job families in place of the existing a priori job families.

The principles given above are very strongly supported by the results of this study. Some investigators have suggested contradictory classification system guidelines based on erroneously equating classification efficiency to predictive validity. But when measurement of classification efficiency is made in terms of MPP, computed after entities have been optimally assigned to jobs, as in this study, DAT principles have been consistently validated.

2. Operational Implications

Design A provides further evidence that the operational AA test composites are grossly inadequate. At the same time, data strongly suggest that the present ASVAB tests have sufficient multidimensionality and differential validity to permit effective personnel classification. In the present study, we see that assignment variables derived from the ASVAB (of the type recommended by DAT) have a 133 percent improvement over the operational AVs. The additional classification efficiency provided by adding all 20 of the Project A concurrent validation experimental variables to the 9 existing ASVAB tests to form a new, much larger, classification battery provides a further gain in MPP of 32.5 percent.

While the procedures used to form the existing operational job families are clearly not optimal, they are much more effective than are the AA composites corresponding to each family. Most of the potential increase in MPP obtainable from using more job families is available from the use of a priori job families that meet other operational needs.

The primary technical report on Project A (McLaughlin, Rossmeissl, Wise, Brandt, and Wang, 1984) concludes that job clustering processes in the context of the same validity data as used for our Design B lacked sufficient stability to warrant confidence that any gains provided would be demonstrable in independent samples. However, the emphasis in McLaughlin, et al. (1984) was on the instability of the regression weights for FLS composites, rather than on the MPP achievable from the optimal assignment of entities in independent samples to alternative job families. DAT favors the latter utility approach over the use of psychometric indices, as favored by McLaughlin et al. (1984), that have no apparent connection to utility.

Operational job families should be based on the use of all available information and must provide for all MOS. This study has not attempted to make maximum use of even the two data sets selected for use with Design A and Design B, let alone make use of all of the validity information available to the Army. Thus, while we believe our findings to be based on

adequately representative data that permit credible conclusions regarding the utility of utilizing more and better defined job families in the Army initial classification system, we do not recommend the installation of the specific job families identified in this study. We instead recommend the integration, through expert judgment, of the information from: (1) our CE job clustering procedure as used on Design A, Design B, and additional data sets; (2) CMF membership of each MOS; and, (3) classification family membership of each MOS. The use of such an integrated approach would readily provide 20 to 30 credibly classification-efficient job families for use in a revised classification system.

IMPROVING CLASSIFICATION EFFICIENCY BY
RESTRUCTURING ARMY JOB FAMILIES

I. INTRODUCTION

A. Objectives

The purpose of this research is to build upon the foundation of differential assignment theory by examining the effects of restructuring Army job families on potential classification efficiency (PCE). Specifically, this research addresses the effects on PCE of (1) increasing the number of job families; (2) employing different job clustering methods to form job families; (3) using full least squares (FLS) composites instead of aptitude area composites for assignment; (4) substituting different criterion measures in the joint predictor-criterion space; (5) increasing the dimensionality of the predictor space; and (6) computing the regression weights of FLS composites on moderately sized analysis samples (as contrasted to the infinitely large analysis samples used in the studies of Nord and Schmitz, 1989, 1991 and Whetzel, 1991).

Focusing on the job family structure is a promising approach to improving classification efficiency. In this research, a new job clustering method is proposed that minimizes the successive reduction in potential classification efficiency in the resulting job families. The goal is to provide a job family clustering method that contributes to an improvement in the ability to classify individuals efficiently and, thus, an increase in overall mean predicted performance (MPP).

B. Theoretical Background

The earliest and most significant contributions to classification research come from the psychometric theories of Hubert Brogden and Paul Horst during the 1940s and 1950s. Their work provides the theoretical foundation for all subsequent research on classification. Building upon the work of these early researchers, Zeidner and Johnson (Johnson & Zeidner, 1990, 1991; Zeidner, 1987; Zeidner & Johnson, 1989a, 1989b, 1991a, 1991b) introduced differential assignment theory (DAT) as part of a revival of classification research within the field of personnel psychology. The following section will provide a brief review of the early work of Brogden and Horst as it relates to the present research. In addition, the following section will

contain a discussion of some of the key principles in differential assignment theory relevant to this research.

1. Linking Classification Efficiency to Performance: Brogden's Allocation Model

Hubert Brogden is responsible for directly tying measurement of classification efficiency to mean predicted performance (MPP) and thus to the utility of classification. Brogden (1946, 1949; see also Brogden & Taylor, 1950) is probably most well-known for his models estimating the utility of selection devices. The utility of a selection device is the degree to which its use improves the quality of the individuals selected beyond what would have occurred had that device not been used (Blum & Naylor, 1968). Brogden (1949) used the principles of linear regression to demonstrate how the selection ratio and the standard deviation of job performance in dollars affect the economic utility of a selection device.

Brogden's concentration on the utility of selection devices led naturally to the expression of classification in the same terms. In 1959, Brogden developed a general allocation model in which he examined the efficiency of classification as a function of the validity of the estimates of job performance, the degree of intercorrelation of these estimates, and the number of jobs. His goal was to show the effects of these variables on productivity when classifying individuals to jobs. He demonstrated that $MPP = R(1-r)^{1/2}f(m)$. In this formula, R is the average predictive validity of the least squares estimates (LSEs) of job performance, r is the average intercorrelation among the LSEs of job performance, and f(m) is an order function which reflects the effects of increasing the number of jobs (m) or job families on classification efficiency.

From this formulation, it is apparent that when R and f(m) increase, MPP also increases. However, note that the lower the intercorrelation among the LSEs, r, the greater the MPP. In practice, it is not unusual to have fairly high intercorrelations among the LSEs. The significance of Brogden's finding is that even when the intercorrelations among the estimates are high, considerable classification efficiency remains. As Brogden points out, even with intercorrelations of .80, classification gains are 45% as great as with intercorrelations of zero. Nord and Schmitz (1989, 1991) found in their empirical study that even with an average r of .95 among the predicted performance LSEs, they were able to obtain considerably greater MPP when LSEs were used for assignment compared to when the U.S. Army's operational composites were used for assignment.

The significance of Brogden's formulation to the present research is that the predictive validity, R, and the average intercorrelation among the LSEs, r, are both affected by increasing the number of job families. Increasing the number of job families in a classification-efficient manner affects validity, R, because it results in more homogeneous jobs being placed together to be predicted by a single LSE. With more homogeneous job families, more precise classification of individuals into those families is possible. This more reliable and precise prediction capability results in an increase in validity (R). Increasing the number of job families in a classification-efficient manner affects the intercorrelation, r, among the LSEs because it results in a greater uniqueness in the job families. Thus, it is possible to capitalize on the differences among the job families resulting in a decrease in the average intercorrelation among the LSEs.

However, Brogden (1959) also demonstrated, through the order function f(m), that even if R and r are held constant, increasing the number of jobs will increase classification efficiency. This effect is analogous to the effect that the selection ratio has on the selection process. For the selection ratio, as the number of applicants increase or the number of available vacancies decrease, more selectivity into these vacancies is possible resulting in an increase in predicted performance. Similarly, as the number of jobs or job families increase, it is possible to more precisely assign individuals to the jobs or job families by capitalizing on intra-individual differences. This greater precision in assignment would also result in an increase in predicted performance.

Brogden (1959) made a number of simplifying assumptions in order to mathematically demonstrate the relationships just discussed. The present research provides a more realistic, empirical test of these relationships. As the number of job families increases, validity should increase and the intercorrelation among the LSEs should decrease. These effects should be manifested by an increase in MPP after optimal assignment to jobs.

2. Horst's Differential Validity Index

Paul Horst (1954) is the primary contributor to the theory and methodology underlying the design of classification-efficient test batteries. The most classification-efficient test battery is one with the greatest differential validity. Differential validity represents the ability of a test to forecast differences in performance in different jobs (Cascio, 1991). A simple example of

the concept of differential validity can be illustrated through a two-job classification problem. For two jobs, A and B, one test would be selected for inclusion in a classification-efficient battery that had a high correlation with performance on job A and a low (or preferably negative) correlation with performance on job B. Then, another test would be selected that had a high correlation with performance on job B and not on job A. The resulting battery would be one with high differential validity. The goal is to be able to predict an individual's relative fitness for job A over job B or vice versa.

Thus, in order to develop classification-efficient test batteries, Horst (1954) needed to first define an index of differential validity to be used for much more complex, realistic test development. Horst's differential index, H_d, can most generally be stated as the sum of the squared correlations between the difference of each pair of criterion scores and the corresponding pair of differences between the best weighted predictors of each criterion. Note that in order to compute a difference between each pair of criterion measures and the best predictor of each difference, it is necessary to have criterion measures for each person on each job. Since this is never possible in actual practice, Horst (1954) stipulates that predicted criteria based on the "least-square" estimates from the test battery be substituted for the unobtainable actual criterion measures. This theorem is a key assumption underlying classification research since without it evaluating the efficiency of various classification batteries and classification procedures would not be possible.

Brogden (1955) provided a rigorous proof of this theorem showing that, for any assignment to jobs, the sum of the multiple regression criterion estimates will equal the sum of the actual criterion scores. This theorem holds because the actual criterion components that are orthogonal to the joint predictor-criterion space are totally irrelevant to either the implementation of a selection/classification process, or to the measurement of process efficiency. The only criterion components that are relevant are within the joint predictor-criterion space, and the correlation of predicted performance with actual performance is unity when computed in the joint predictor-criterion space. When both the predictors and the predicted criteria are the least square estimates (LSEs), Horst's index simplifies to the average squared difference between each pair of criterion measures.

Horst's differential index, H_d, plays a key role in the present research because it is H_d that is maximized in the classification-efficient job clustering algorithm developed for this research. Thus, although H_d is typically used for selecting the most classification-efficient tests for a test battery, the present research is designed to demonstrate that H_d can also be used in forming classification-efficient job families.

The purpose in forming classification-efficient job families with the use of H_d is to provide an increase in MPP. Horst (1954) was simply defining a psychometric index and provides no link to the measurement of MPP. However, it has been demonstrated that Horst's differential index can be directly linked to MPP, and thus to utility, through its relationship to Brogden's measure of classification efficiency (Johnson & Zeidner, 1990, 1991).

Brogden's 1959 model is based on a set of assumptions regarding the relationships among and across predictor and criterion variables (Johnson & Zeidner, 1990, 1991). These relationships can be depicted in terms of Spearman's Two Factor theory. Brogden's assumptions are met if: (a) the factor matrix, F_v, is a matrix such that F_vF_v' is equal to C_p (the covariances among predicted performance scores), (b) all elements of the first general factor (the g factor) from F_v are equal to the product $R(r)^{1/2}$, and (c) the *remaining* factors (specific unique factors) from F_v can be expressed as a diagonal matrix with the diagonal elements equal to $R(1-r)^{1/2}$. It is possible to show a link between Brogden's model and Horst's differential validity index because Horst's H_d is equal to the sum of the squared deviations from the column means of each element of F_v. The sum of squared deviations for the first column of F_v (the g factor) is equal to zero, and the sum of the squared deviations for the remaining m columns of F_v (the unique factors) is $R(1-r)$. Thus, H_d is equal to (m-1) times $R(1-r)$ when Brogden's assumptions are met. Brogden's complete formula for mean predicted performance is: $MPP = R(1-r)^{1/2}f(m)$. Therefore, when substituting Horst's index it is only necessary to take the square root of H_d, divide by (m-1), and multiply by f(m) to obtain MPP when Brogden's assumptions are met. Thus, it is reasonable to expect, to the extent that Brogden's model is robust with respect to his assumptions, that H_d closely approximates MPP. Even though we know Brogden's assumptions are rarely met in empirical data, we can still expect that the utilization of a clustering method that increases H_d will also increase MPP. Similarly, other trends such as the increase in the

number of job families that result in an increase in H_d, can be expected to provide a similar increase in MPP.

3. Concepts and Principles of Differential Assignment Theory

Differential assignment theory (DAT) can be defined by four organizing concepts: (1) to maximize benefits, a set of quantitative principles must be employed that embrace selection of predictors in a battery, the structure of job families, and the strategies and algorithms used in the selection/assignment process; (2) utility models, measuring benefits in terms of mean predicted performance, provide the best approach for specifying personnel selection policies and procedures for operational systems; (3) benefits for both selection and classification procedures are maximized by using the same weights for a given set of composites under optimal conditions, while under non-optimal conditions, selection and classification must be separately considered; and (4) any multidimensional selection/classification strategy and algorithm can be practically implemented in operations by utilizing available computer capabilities.

Several of the key principles of DAT are directly relevant to the current research. At the core of DAT is the principle of multidimensionality in the joint predictor-criterion (JP-C) space. It is this principle that serves as the theoretical foundation of DAT with regard to the nature of human abilities. DAT assumes a non-trivial degree of multidimensionality in the joint predictor-criterion space. This means that differential assignment theory assumes there are other factors besides the "g" factor (general cognitive ability) that can play a significant role in the selection and classification process. This assertion is counter to the consensus established in recent decades that a general cognitive ability component is sufficient for predicting job performance in all jobs (see the Special Issue of the Journal of Vocational Behavior, 1986, for a collection of opinions).

Indeed, since the advent of the type of validity generalization (VG) research introduced by Frank Schmidt and John Hunter in the 1970s (Schmidt & Hunter, 1977), there has been increasing support among measurement specialists for the sole use of g for predicting job performance. Current VG theory, as contrasted with Mosier's (1951) earlier concept, is founded on the principle that the g factor has an overriding influence on performance, and it is this common element among jobs that enables validity to be generalizable across different jobs and situations.

DAT is enriched by broadly based VG concepts and findings. However, the VG emphasis on the g factor, or on g plus one or two additional group factors, prevalent among strong proponents of VG theory, is not a requisite characteristic of DAT. While the theory is not restricted to any particular factor structure, the assumption of a non-trivial degree of multidimensionality in the JP-C space is essential.

Recent research has shown that contrary to the belief of many VG theorists, it is possible to demonstrate a non-trivial degree of multidimensionality in the JP-C space. Whetzel (1991) factored the predictor-criterion covariances of the same U.S. Army Project A concurrent validation database used in the present research. The matrix of predictor-criterion covariances in this database were factored and rotated such that Horst's differential index was maximized in each successive factor (Zeidner & Johnson, 1989b, 1991b). This factoring was done in order to identify the most classification-efficient factors in the joint predictor-criterion space and to identify representative jobs that loaded differentially on these factors. Whetzel (1991) found that the first factor, the g factor, accounted for 79 percent of the variance. However, with the first factor removed it was determined that six factors contained jobs that loaded highly and differentially on these factors and, therefore, yielded a classification-efficient solution. These results meant that there were six non-trivial dimensions, besides the g factor, within the joint predictor-criterion space. For the present research, it is possible to examine the effects of changing the dimensionality of the JP-C space in two different ways. One way is to compare assignment using the standard Armed Services Vocational Aptitude Test Battery (ASVAB) with assignment based on the ASVAB augmented by 20 new experimental predictors. The experimental predictors should expand the dimensionality of the JP-C thereby providing for more efficient classification. Another way of expanding the joint predictor-criterion space that will be used in the present research is to increase the number of job families in a classification-efficient manner. As the number of job families is increased, each job family will become more homogeneous within itself (more unique components and less g). Each job family will also become more heterogenous with respect to other job families if the job families are formed by taking differential validity into account. In other words, the idea is to expand the joint space by forming job families that are maximally different from one another.

Another of the key DAT principles states that the "best" selection and/or assignment variable for maximizing either selection or classification efficiency is a full least squares (FLS) regression composite. Note that this is a "full" composite, meaning that all of the tests in the battery are to be included. A common misconception is that selected elimination of composites in a battery to reduce the intercorrelations of test composites is helpful or even necessary to increase classification efficiency. A set of FLS composites cannot be improved with respect to classification efficiency by the elimination of tests that measure only g, or of any other tests that might reduce the intercorrelation of test composites (Zeidner & Johnson, 1989b, 1991b).

There have been two empirical studies that have examined the potential of an FLS composite for maximizing classification efficiency. Sorenson (1965) used simulation techniques to compare the allocation to jobs based on full regression equations using all tests of the Army Classification Battery instead of allocation based on two-test aptitude area composites. Sorenson (1965) found that the gain in MPP over random assignment more than doubled by substituting full regression equations for the aptitude areas. Nord and Schmitz (1989, 1991) simulated the assignment of individuals to jobs in a very similar way to that used in the present research. However, they used FLS composites with regression weights based in the nine aptitude area composites, rather than directly on the ASVAB test scores. Nord and Schmitz (1989, 1991) found gains in MPP of over 72% by using FLS assignment instead of the current U.S. Army aptitude area composites. In the present research, a condition has been built into the design that allows for another comparison of assignment with FLS composites instead of the current U.S. Army aptitude area composites. However, unlike Nord and Schmitz (1989, 1991) the FLS equation is based directly on the ASVAB test scores which should provide for even greater expected gains in MPP.

Finally, the most relevant differential assignment principle for the present research is the principle which states that, in general, increasing the number of assignment composites and associated job families adds to potential classification efficiency. It is important to realize that the magnitude of a gain in potential classification resulting from an increase in the number of job families will depend on the method used to provide more job families and upon the heterogeneity of the jobs in the joint predictor-criterion space. One of the best ways of restructuring jobs in order to increase potential classification efficiency should be to reconstitute

a total set of jobs into classification-efficient clusters. It is this last principle that is most directly examined in the present research through the development of a classification-efficient method of job clustering and use of a set of conditions to demonstrate the expected increase in MPP as the number of job families increase.

C. Alternative Approaches for Improving PCE

There are many alternative approaches that could be employed to bring about improvements in the selection and classification system of an organization such as the U.S. Army. By far the largest improvements in personnel classification efficiency would come from the substitution of FLS composites for the existing U.S. Army aptitude area composites. However, there are a number of other promising changes that could provide appreciable amounts of improvement in productivity that, for the most part, are additive to the gains due to the use of FLS composites. Improvements could result from the creation and use of: a classification-efficient (CE) test battery, more and better job families, better CE test composites as assignment variables, and more effective assignment strategies.

1. Changing Test Battery Content

A set of test composites can provide no more PCE for a prescribed set of job families than was provided in the test selection process that created the operational test battery. If it is possible to change the content of the operational test battery, improvements in PCE could be accomplished by selecting predictors that experts believe have a high degree of differential validity (as contrasted with predictive validity) for inclusion in an experimental test pool. It would then be possible to perform test selection employing indices that measure PCE to create an operational battery with the best PCE.

Recently, Johnson, Zeidner, and Scholarios (1990) completed a study that compared various test selection indices in terms of their potential for maximizing PCE. From an experimental test pool of 29 tests (including the 9 ASVAB tests), tests were selected to create FLS composites of five or ten tests. These test batteries were then used in the simulated assignment of individuals to jobs and MPP was calculated to assess the efficiency of that assignment. Two of the indices used to select tests were Horst's differential index, H_d, and

Max-PSE which is a measure of selection efficiency. Use of the classification-efficient index, H_d, resulted in gains in MPP as great as 22% over the use of the selection-efficient index, Max-PSE. Additionally, this study showed gains in MPP of approximately 25% when the number of FLS predictors was increased from five to ten. Overall, it was concluded that classification-efficient methods of test selection lead to greater MPP in an assigned group than a selection-efficient method.

2. Restructuring Jobs into New Job Families

If an operational test battery were fixed and could not be readily changed, PCE could still be improved by efficiently increasing the number of job families with their associated predictor composites. It is estimated that an increase in the number of composites and associated job families to somewhere between 20 and 40 would most likely provide the maximum efficiency for Army jobs. In the present research, classification-efficient job families will be created using H_d that can be compared to job families formed using a selection-efficient method. These empirical methods of forming job families will also be compared to the job family structures currently used by the U.S. Army.

3. Changing Assignment Variables

The most important change in assignment variables that could be adopted by the Army would be the conversion of the existing aptitude area test composites into least squares estimates based on all tests in the classification battery, i.e., using predicted performance as the basis of assignment rather than test composites. These full least squares (FLS) composites are optimal for both selection and classification of personnel.

The use of numerous test composites would require the Army to record many scores on each soldier's official record. One way to use many assignment composites would be to install a two-tiered system in which the large number of FLS composites are used to make recommendations regarding assignment, while a much smaller number of factor scores are used for counseling. These factor scores would also be used as a basis for setting minimum cutting scores for entry into special training programs, as a career planning aid to be available to the soldier, and for other personnel management purposes, such as retention and promotion. A study is currently underway to assess the amount of PCE that can be provided by a small

number of factor scores. This study is designed to compare the PCE provided by a number of different types of assignment composites.

4. Changing Selection-Assignment Strategies

Improvements in PCE could be made through the consideration of different selection/assignment strategies. One simple selection/assignment method would be a two-stage strategy in which applicants are selected based on a single predictor and then assigned to specific jobs using multiple assignment variables. However, a possibly more efficient selection/assignment strategy for practical implementation would be a simultaneous selection and optimal classification system called the multidimensional screening (MDS) procedure (Johnson & Zeidner, 1990, 1991).

The MDS procedure is best understood in the context of Brogden's (1959) model where each predictor is an FLS composite yielding a score that divides into a general (g) and a unique (u) component. Brogden (1959) discussed an assignment strategy in which applicants are simultaneously selected and classified into jobs using only the unique components, and he states that "removal of the common component will be shown to have no effect on the classification of [individuals] or on the allocation average" (p. 184). MDS is a modification of Brogden's model to reflect a simultaneous strategy in which selection and classification is accomplished using a separate FLS composite for each job that incorporates both the g and u components. This strategy is an important improvement in Brogden's model because it allows for a larger gain in mean predicted performance due to selection when g constitutes a large part of each score (as is usually the case).

Whetzel (1991) completed a simulation study that compared three methods of selection/assignment: selection on g and then assignment on the FLS composite (two-stage strategy); selection and assignment based only on g; and simultaneously selecting and assigning on FLS (multidimensional screening). Whetzel (1991) found that MDS was far superior in terms of gain in MPP compared to selecting and assigning solely on g. MDS was also statistically greater in terms of gains in MPP than selection on g and assigning on FLS, but the gains were more modest. It was concluded from this study that the largest and most dramatic increase in MPP comes from the use of FLS composites in a two-stage selection/classification process. A

smaller, but still worthwhile, improvement results from the integration of selection and classification procedures using the MDS algorithm.

5. Changing Criterion Variables and Increasing Validity Information

Finally, all approaches relating to a redesign of the classification system could be made more effectively, providing greater classification efficiency, if: (1) the criterion variables were more reliable and more accurate measures of the value of the individual in the accomplishment of the mission; and (2) the analysis samples on which validity data are computed were larger. Our knowledge of the effect of sample size on the stability of regression weights is extensive. However, this knowledge does not translate to predicting the effect of analysis sample size on MPP after optimal assignment of a pool of candidates to jobs. While we do not in this study directly measure the impact of criterion quality and the size of analysis samples on MPP, further insight on this issue can be obtained from this study.

D. Current Trends

1. Validity Generalization

In recent decades, there has been a steady decline in research and application pertaining to classification. The most popular trend in personnel research in recent decades has been the validity generalization movement (Schmidt & Hunter, 1977). The research that has come out of VG has led to the conclusion that there is an all-pervasive general cognitive ability (g) component that is the best measure for predicting job performance. Although general cognitive ability contributes substantially to efficient selection, it leaves little room for classification and has led to a general pessimism on the part of many researchers about the future usefulness of classification batteries. This pessimism is unfounded, however, and is due mainly to misunderstandings about classification. Differential assignment theory has been introduced to dispel some of these misunderstandings and to demonstrate the tremendously important role that classification can play in the overall utility of a complete personnel utilization system.

There is a general resistance to DAT mainly because there is a tendency to confuse it with what is often called either "specific aptitude theory" or "differential aptitude theory" (see Schmidt, Hunter, & Larson, 1988). Specific aptitude theory had its origins with the work of

researchers such as Guilford (1956, 1957, 1959), Hull (1928), and Thurstone (1938). The idea behind specific aptitude theory is that there are certain aptitudes that should be relevant for predicting performance on certain jobs. Thus, a math test should predict work requiring numerical skills while a verbal test should predict work requiring verbal skills. Under ideal circumstances, each test would measure a separate aptitude, thus mandating low intercorrelations among the tests. A composite of these tests could be constructed through the use of multiple regression in order to predict success in the job or job family for which it was constructed. In 1928, Clark Hull published a book on aptitude testing in which he stated his differential aptitude hypothesis. This hypothesis asserts that a tailored composite of specific tests could make an incremental contribution to the prediction of performance over and above the contribution of general cognitive ability. Through the use of factor analysis, a great deal of research was done to identify specific aptitudes that represented the structure of human abilities. These specific abilities were needed in order to build tailored aptitude test batteries consistent with specific aptitude theory. Thurstone's (1938) studies resulted in the identification of seven factors which he termed the "primary mental abilities". Guilford (1956, 1957, 1959) presented a scheme to classify known factors of intelligent behavior that resulted in a theoretical representation of the structure of the intellect composed of 120 different factors.

DAT is different from specific aptitude theory in two major ways. First, in constructing a classification test battery, emphasis is placed on accentuating the differences between predicted measures of success. Horst's (1954) differential validity index facilitates the selection of predictors for inclusion in such a classification-efficient test battery. The goal is to have a set of predictors that capitalizes on any and all inter- and intra-individual ability differences. It is not necessary for each predictor to represent a different aptitude, and it is not necessary that the predictors have low intercorrelations. Brogden (1951, 1959) demonstrated that high predictor intercorrelations do not reduce classification efficiency as much as previously thought.

The second major way that DAT is different from specific aptitude theory is that in order for differential assignment to be maximally efficient, full least square regression equations (FLS) should be used as the best estimate of actual criterion performance. This is contrary to specific aptitude theory which has been implemented through the use of unit-weighted composites consisting of a reduced number of tests than are in the total battery. Allocation to jobs based

upon a full least square regression equation for the entire battery provides for maximally efficient assignment according to differential assignment theory.

Another misunderstanding about classification research is the belief that predictive validity can be used to evaluate the effectiveness of classification. Some recent articles discussing classification effects in terms of predictive validity include Hunter (1986), Schmidt, Hunter, and Larson (1988), and Thorndike (1986). A more appropriate figure of merit for evaluating classification effects is mean predicted performance (MPP). When dealing with a simple univariate selection model, the validity coefficient is directly proportional to MPP when the selection ratio is held constant and the relatively simple optimal selection algorithm is used (i.e., the rank ordering of applicants on predicted performance and selection in order from the top down). However, when dealing with a more complicated multivariate model required for classification there are no simple analytical methods for computing MPP. In fact, the only practical solution is to use real or synthetic data as input into simulations of personnel utilization strategies. MPP can then be calculated from the simulation to evaluate potential classification efficiency (PCE) of various personnel assignment strategies. What may not be obvious is that predictive validity is relegated by the underlying mathematics to what in many cases may be a minor role in achieving an increase in classification efficiency. Under certain conditions, one set of test composites having a smaller average predictive validity than another could actually possess greater classification efficiency (Zeidner & Johnson, 1989b, 1991b).

The trend in recent times is to devote all attention to increasing the predictive validity of test batteries without concern for differential validity needed for efficient classification. This trend is due primarily to the emphasis that VG places on a dominant g factor. The development of aptitude test batteries in the U.S. Army over the years has certainly been affected by this trend. One of the Army's first set of aptitude tests was the Army Classification Battery (ACB). As the name suggests, there was considerable emphasis placed on the ACB's ability to classify individuals into jobs efficiently during the first fifteen years of its use (Zeidner, 1987). Unpublished Army studies show a generally declining trend in the amount of classification efficiency present with each change of ACB content during the period that the ACB was being transitioned into the current ASVAB. Furthermore, the use of unit-weighted aptitude area composites further erodes the classification potential of the ASVAB. This trend has continued

with the experimental pool of predictors developed recently for the U.S. Army's Project A. These predictors were assembled with the goal of increasing predictive validity, rather than differential validity (McHenry, Hough, Toquam, Hanson, & Ashworth, 1990).

2. Decreasing the Number of Job Families

Another disturbing trend in recent times is the tendency for researchers to favor decreasing the number of job families in operational systems. This trend, once again, is caused primarily by a focus only on selection efficiency and increasing support for general cognitive ability as sufficient for predicting performance in all jobs. The result of considering the g factor as the only significant predictor of performance in all jobs is that the differences between jobs are diminished and the need for numerous job families decreases.

The Army currently has nine job families, the Navy has 11 families, the Air Force has four families, and the Marines have six. Other large organizations have similarly fairly small numbers of job families. For example, the Office of Personnel Management (OPM) has recently found seven job families to be representative of the professional and administrative jobs in the federal government (Rheinstein, McCauley, & O'Leary, 1989b). These job families were used in the development of the new Administrative Careers with America examination. The Department of Labor, based on the research of Hunter (1983), is using five job families (clustered by job complexity, rather than by job similarity) to represent all 12,000 jobs in the Dictionary of Occupational Titles.

Thus, there is a tendency for job family systems developed for large organizations in recent times to include, on the average, approximately four to seven job families. The Army and the Navy are the exceptions in that they are still using 9 and 11 job families, respectively. However, there have recently been serious suggestions that the Army decrease their number of job families to four (McLaughlin, Rossmeissl, Wise, Brandt, & Wang, 1984).

The Air Force currently has four job families that match the number of strong group factors in the ASVAB. Some believe that basing the number of job families on the number of strong factors in the test battery is the most appropriate method. One of the main purposes of the present research is to demonstrate that it would be a serious mistake for the U.S. Army to decrease their number of job families to four. Decreasing the number of Army job families would result in a further erosion of any classification potential in the Army's

selection/assignment system. This research is designed to demonstrate that actually increasing the number of job families beyond the current nine could begin progress towards a more optimal selection/assignment system for the U.S. Army.

E. Research Approach

This research utilizes a model sampling approach combined with a computer simulation of the selection and classification process. Model sampling involves the generation of synthetic entities that have specified statistical characteristics in common with empirical random samples drawn from the empirical sample. In this approach, actual empirical databases with covariances between predictors and criteria provide the parameter values that define the designated population. These parameters form the basis for the generation of synthetic entities with test scores that have the same expected means and covariances as the designated population. The parameters of the synthetic samples differ from those of the designated population by an amount of sampling error that is related to sample size as though they were empirical samples. This model sampling approach has many advantages over simply using existing empirical database scores in the simulations.

Model sampling provides increased flexibility in that samples of any number and size can be generated for any universe, including a current or future youth population, if that universe can be defined by both the covariances among the relevant predictor variables and the validities of these variables against all criterion components. It could be argued that the shape of a score distribution would be more realistic for a simulation using empirical scores rather than synthetic scores generated to have a normal distribution. However, with a little extra effort, synthetic scores can be generated to reflect any degree of censoring that is desired, and has the added advantage that distributions can be produced that are closer to a distribution of a future population than is provided by the detailed shape of the distributions of the past years. Finally, model sampling allows the evaluation of conditions which could affect the system but are not available in terms of actual empirical data.

For the present research, the primary advantage of the model sampling approach is that a cross-validation design can be utilized that provides a rigorous methodological investigation

of the various experimental conditions in this experiment. For one set of conditions in this research, model sampling allows the generation of an analysis sample independent of the designated population for use in job clustering and definition of assignment variables. For all conditions, the model sampling approach allows the generation of 20 independent cross-samples that vary in size depending upon the demands of the design. Thus, by using model sampling techniques it is possible to essentially replicate each condition in this experiment 20 times.

The model sampling technique used in this research is made more credible by the realism of the designated population made possible by two empirical databases from the Army Selection and Classification Project (Project A). The two parts of this research, Design A and Design B, make use of the two databases differently. Design A is based upon the 18 jobs investigated in the concurrent validation phase of Project A (Campbell, 1990). Although data were collected for only 18 jobs in this phase, validation data on 20 new experimental tests with carefully designed performance criteria is available in this database.

For Design A, the same 18 jobs also were extracted from the second database from the early stages of Project A called, for the purposes of this research, the "McLaughlin" database (McLaughlin, Rossmeissl, Wise, Brandt, & Wang, 1984). The "McLaughlin" database contains validation data for the ASVAB and the Skill Qualification Test (SQT) and training score criteria. The "McLaughlin" database is utilized in Design A to compare the use of the less appropriate SQT criterion (constructed for use as a training diagnostic tool) with the specially developed Core Technical Proficiency (CTP) criterion developed in the concurrent validation phase of Project A.

However, the "McLaughlin" database plays an even more important role for Design B. The "McLaughlin" database contains validation data for over 98 jobs of which 60 jobs were selected for this research. The availability of 60 jobs with validation data based on moderately large sample sizes is very important to the operational implications of this research. It makes it possible to compare much more substantial and realistic sets of operational and empirical job families than is possible with the more limited set of jobs in Design A. Both databases will be described in more detail in the next chapter.

In Design A, three primary areas relating to job structure are investigated. First, it is expected that there will be a significant improvement in MPP as the number of job families to

which individuals are classified increases. For Design A, the number of job families will increase from 6 to 9 to 12. Second, it is expected that there will be significantly greater improvement in MPP with jobs empirically clustered into job families specifically to maximize classification efficiency compared with jobs empirically clustered into job families specifically to maximize selection efficiency. Third, the empirical methods of job clustering developed here are expected to result in significantly greater improvement in MPP than the operational job families currently being used by the U.S. Army.

A number of secondary areas also are investigated in Design A. In Design A, it is possible to examine whether the efficiency of classification varies with the number of job families according to a negatively accelerated function. This idea was originally proposed by Brogden (1959). It is expected that the increase in MPP from 6 to 9 job families will be greater than the increase in MPP from 9 to 12 job families. In addition, Design A examines the effects on classification efficiency of expanding the number of predictors from nine ASVAB tests to nine ASVAB tests plus 20 experimental predictors. It is expected that the expanded predictor space will provide an improvement in MPP compared to the use of only the ASVAB. Design A also contains a set of conditions to compare the use of FLS composites instead of aptitude area composites for assignment. It is expected that the use of FLS composites will result in significantly greater improvements in MPP than the current aptitude area assignment system. Finally, in Design A, the effects on classification efficiency of using the SQT criterion instead of the CTP criterion are investigated. It is expected that substituting the SQT criterion for the CTP criterion will result in no differences in the conclusions reached about any of the primary or secondary areas just discussed.

In Design B, it is important to demonstrate the job clustering methods with a large number of jobs. The other expectations in Design B are similar to Design A in that (1) the magnitude of the MPP scores are expected to increase as the number of job families increase, and (2) the empirical methods of forming job families will be compared to the operational job families currently used by the Army. In Design B, however, the number of job families will be increased from 9 to 16 to 23. This increase provides a further opportunity to examine Brogden's proposal that the efficiency of classification varies with the number of job families

according to a negatively accelerated function. Hopefully, some conclusions can be reached about the efficiency of utilizing as many as 23 different job families from Design B.

II. RESEARCH METHOD

A. Data Description and Corrections

Two empirical databases will be utilized in the present research. Both of these databases were part of the Army Selection and Classification Project (Project A). The first data set used in this research comes from the Project A effort to generate new predictor and criterion measures to enhance the selection and classification system for all entry-level positions in the United States Army. In a concurrent validation phase of Project A, the ASVAB along with new predictor and criterion measures were administered to incumbents who entered the Army in 1983 or 1984. This data set forms the first database used in the present research and will be called simply the "Project A" data set.

The second data set comes from the early stages of Project A which concentrated on validating the current ASVAB aptitude area composites and considering alternative composites of the ASVAB. For this purpose, available computer records containing ASVAB predictor scores along with criterion measures consisting of training school grades and the Skill Qualification Test (SQT) were drawn for people who joined the Army in 1981 and 1982. The analysis of these data are reported in McLaughlin, Rossmeissl, Wise, Brandt, and Wang (1984). These data form the second database used in the present research and will be called the "McLaughlin" data set.

1. Job Sample

The Project A concurrent validation data set contained validation data for 19 Military Occupational Specialties (MOS). There was only one modification made to this database for the present study. One of the MOS, 51B Carpentry and Masonry Specialist, was not used in this study because it had a very small sample size (n=69) compared to the other MOS in the database, and it resulted in an unstable factor structure when its use was attempted in previous research (Whetzel, 1991). The "McLaughlin" data set contained validation data for 98 MOS. Of these 98 MOS, the same 18 jobs contained in the Project A concurrent validation sample

were selected for the first part of this study (Design A). An additional 42 MOS forming a total set of 60 jobs were selected for the second part of this study (Design B). The total number of jobs was set at 60 because it was originally estimated that the largest number of job families that would be created would be approximately 30 job families. A reasonable number of jobs was determined to be at least twice the number of job families.

The additional 42 jobs selected to compose the "McLaughlin" database for Design B were chosen out of the possible 98 available MOS in a two stage selection process. In the first stage, all jobs with a sample size greater than 200 were selected. Including the original 18 Project A MOS, this process identified 50 jobs. Two jobs were eliminated because they did not have reliability information. Five jobs were eliminated because they shared obvious similarities to jobs already included in the database (e.g., three personnel jobs and two helicopter repair jobs). Thus, at the end of the first stage there were 43 candidate jobs. In the second stage, the remaining jobs were reviewed as candidates to complete the set of 60 jobs. The following criteria were used in selection: (1) desire to include jobs that were in as many of the different Career Management Fields (CMF) as possible; (2) availability of reliability data; and (3) sample sizes close to or greater than 100. Using these criteria, 17 additional jobs were selected to complete the set of 60 jobs.

Appendix A (Table A-1) lists the 18 jobs contained in the Project A concurrent validation data set along with the sample sizes for these 18 jobs for both the Project A data set and the "McLaughlin" data set. Note that the average sample size per job for the Project A data set was 388 and the average sample size per job for the "McLaughlin" data set is 2,370. Appendix A (Table A-2) lists the total set of 60 jobs and their sample sizes for the "McLaughlin" data set. The average sample size across these 60 jobs is 1,002.

2. Predictors and Criteria

For this study, the Project A concurrent validation predictors included the nine ASVAB tests plus an expanded set of 20 additional experimental predictors. These new predictors were designed to capture cognitive and noncognitive abilities not covered by the ASVAB: spatial visualization and orientation, perception and psychomotor skills, temperament/personality, vocational interest, and job orientation. Appendix B (Table B-1) lists the ASVAB tests and the

20 additional predictors along with their reliabilities. The "McLaughlin" predictors included only the ASVAB tests.

The criterion measures used in this study were Core Technical Proficiency (CTP) for the Project A concurrent validation data set and the Skill Qualification Test (SQT) for the "McLaughlin" data set. Three jobs that matched the Project A jobs in the "McLaughlin" data set lacked SQT scores, so end-of-course training scores were substituted for these jobs.

The CTP criterion was chosen for this study instead of one or more of the other four criterion components developed as part of the Project A concurrent validation effort because it represents MOS-specific performance. The CTP criterion was designed to measure the proficiency with which the soldier performs the tasks that are "central" to the MOS (Campbell, Ford, Rumsey, Pulakos, Borman, Felker, DeVera, & Riegelhaupt, 1990). It is composed of both hands-on and paper-and-pencil measures of MOS-specific task proficiency. The MOS-specific aspect of the CTP criterion is important because it provides for greater multidimensionality in the joint predictor-criterion space. It is desirable to have a criterion that differentiates between jobs to demonstrate classification effects. Evidence from previous research supports the notion that CTP is better for differentiating between jobs. Wise, Campbell, and Peterson (1987) reported that the optimal component for differentiating between jobs was CTP, with the four other components showing little added value for this purpose. In addition, in a preliminary factor analysis done as part of the Whetzel (1991) study, it was found that when all five criteria were used in factoring the predictor-criterion covariances, a strong simple structure did not emerge. In other words, jobs did not load highly on one factor and near zero (or at least much lower) on all other factors, hence the loadings did not show distinct differentiation of jobs on the factors. There was much better differentiation found when the CTP criterion was used alone. The reliability of the CTP criterion used for the present study was .85 (Zeidner,1987).

The SQT criterion measure available in the "McLaughlin" data set also represents MOS-specific performance. SQTs have been administered by the Army since 1977 to assess soldiers' qualifications for promotion and to evaluate the overall effectiveness of Army training programs. Each year a separate SQT is constructed for each MOS and skill level within that MOS. SQTs may sample from 12 to 36 tasks, and soldiers are allowed to prepare in advance for the tasks

to be tested. A test may consist of both hands-on and paper-and-pencil job knowledge items. However, for the period of data covered in the McLaughlin et al. (1984) analyses, only paper-and-pencil job knowledge items were available.

The "McLaughlin" database also contained end-of-course training scores. These are tests that are developed at the schools for the purpose of testing whether the students have learned what had been taught. McLaughlin et al. (1984) used a combination of the two criterion measures for several of their analyses. For the present study, it was decided that the SQT criterion measure would be preferable to a combined criterion or the end-of-course training scores alone. There were two reasons for this decision. First, although both the SQT measures and the end-of-course measures are essentially criterion-referenced tests, the SQT measures appeared from McLaughlin et al. (1984) to be better psychometrically yielding a higher average validity. Second, after some investigation it was discovered that it was possible to obtain fairly accurate estimates of reliability for the SQT criterion but not for the end-of-course training criterion. Reliability estimates were needed for all of the criterion measures used in this study so that corrections for criterion attenuation could be made.

These reliability estimates were obtained by contacting the U.S. Army Training Support Center in Fort Eustis, Virginia. It was discovered that, since 1987, the U.S. Army has been collecting extensive reliability information for the SQTs. For the present study, Cronbach alpha reliability estimates were obtained for the SQTs corresponding to each of the 60 MOS for the years 1987, 1988 and 1989. There were only 10 MOS without reliability estimates for all three years. Appendix C contains the reliability information across all three years for the 60 jobs in the "McLaughlin" data set.

These Cronbach alpha reliability estimates proved to be the best information available about SQT reliability so it was decided to correct each MOS in the "McLaughlin" database for criterion attenuation based upon the average reliability for that MOS across the three years. Having three years of data should provide a consistent enough estimate of reliability to compensate for the fact that SQTs are changed from year to year with the actual data being used in this study from 1981 and 1982. It is encouraging to note that the average reliabilities across MOS were consistent across the years. The average alphas for 1987, 1988, and 1989 were .83 ($n=2688$), .83 ($n=2893$), and .81 ($n=3018$), respectively.

As mentioned, there were three MOS (16S, 76Y, and 91A) in which end-of-course training data was used instead of SQTs. Obtaining reliability data for these jobs presented an additional problem because the training schools for these MOS indicated that there was no reliability data available. Therefore, it was decided that the SQT reliability data would have to be used as a best estimate of training reliability. However, from the McLaughlin et al. (1984) report it was apparent that the end-of-course criterion data were probably much less reliable than the SQT criterion data. The average adjusted training criterion validity in McLaughlin et al. (1984) was .40, while the average adjusted SQT validity was .46. In order to remedy this problem, an adjustment was made to the reliability estimates for MOS 16S, 76Y, and 91A based on a ratio of how much lower the reliability of the training data would have to be to obtain a validity estimate .06 points lower. Without this adjustment, the reliability of the criterion for the MOS 16S, 76Y and 91A would be greater than their corresponding validities indicate so that the subsequent correction of these validity values for criterion unreliability would be less than it should be. Thus, this problem would introduce an inconsistency between these three MOS and the other MOS. This adjustment resulted in reliability estimates of .58, .66, and .62 for MOS 16S, 76Y, and 91A, respectively.

3. Data Corrections

Both of the Project A concurrent validation and "McLaughlin" data sets must be corrected for restriction in range and criterion attenuation. For the Project A data set, all corrections were done as part of an earlier study for the Institute for Defense Analyses (Johnson, Zeidner, & Scholarios, 1990). These corrections will be described below. The corrections to the "McLaughlin" data set were done for the purposes of the present research.

One other set of corrections will also be described in this section that were discovered to be necessary during the research done by Whetzel (1991). For the Project A data, when the covariances among the predicted performance scores, C_p, were factor analyzed it was discovered that three of the eigenvalues of C_p were negative. This indicated that the V matrix (validity matrix) used for these calculations was not positive semi-definite. This problem can arise from computing validities against the different job criteria on separate samples of individuals, as contrasted with the ideal research situation in which all validities are computed on the same set of individuals.

a. Corrections for Restriction in Range

A matrix of ASVAB (form 8) intercorrelations for a national sample of American 18-23 year olds was used as the "1980 Reference Youth Population" (Mitchell & Hanser, 1984). The availability of the ASVAB youth population intercorrelation matrix enabled the nine ASVAB tests to be treated as "explicit" predictor variables, i.e., variables drawn from an unrestricted population (Appendix D, Table D-1 contains the 1980 youth population intercorrelation matrix). For the Project A concurrent validation data, the 20 experimental predictors were treated as "implicit" predictor variables since the degree of their restriction was determined entirely as a function of their correlation with the explicit variables that are directly restricted by the selection process. The correction procedure is based on Lawley's (1943) assumption that the regression of the implicit predictors on the explicit predictors is linear and that the covariances of the restricted variables exhibit homoscedasticity. Gulliksen's formulae (1950, p.165, numbers 37 and 42) were applied to the youth population covariance matrix for the ASVAB tests (explicit variables) and the covariance matrix for the 20 Project A predictors (implicit variables) for the aggregate of the 18 MOS. The result was a corrected variance-covariance matrix that was then easily converted into correlation coefficients forming the corrected intercorrelation matrix (R_t) of 29 predictors (see Appendix D, Table D-2).

The same Gulliksen formulae were then used to correct the validities for implicit restriction in range effects on the criterion in Project A. In this case, all predictors were treated as explicit variables and only the criterion was implicit. Once again it was then an easy procedure to convert the covariance matrix for the unrestricted predictors and the implicitly restricted criterion into a matrix of unrestricted (population) validity coefficients for each MOS (V). For the "McLaughlin" data set, the correction for restriction in range involved only this second procedure. In the "McLaughlin" data set, there were only the nine ASVAB tests as predictors and the youth population intercorrelation matrix among the tests formed the R_t matrix. The computation of the V matrix (of correlation coefficients) came directly from the covariance matrix for the population predictors and criterion.

b. Corrections for Criterion Unreliability

The validity matrices for both data sets were then further corrected for criterion unreliability. These corrections were accomplished using the general formula with the validity

coefficients in the numerator and the square root of the respective component reliabilities in the denominator. For the Project A concurrent validation data set, a criterion reliability of .85 was used in the corrections for the CTP criterion (Zeidner, 1987). As described earlier, for the "McLaughlin" criterion, each MOS was corrected separately based on the reliabilities given in Appendix C. Appendix D (Tables D-3 and D-4) contain the corrected validity matrices for the Project A concurrent validation and "McLaughlin" data sets.

c. The Positive Semi-definite Condition

It is easily demonstrated that any matrix which is a product of real numbers premultiplied by the transpose of that matrix can have no negative eigenvalues (see Appendix E). This condition of having all eigenvalues equal to either positive real numbers or zero is referred to as being positive semi-definite. The 29 by 29 matrix of correlation coefficients among the Project A concurrent study predictors remained positive semi-definite after corrections for restriction in range and criterion unreliability. No adjustment was required for the 29 by 29 R_t matrix used in the model sampling experiment reported by Johnson, Zeidner, and Scholarios (1990). The covariances among the predicted performance variables, C_p, were not utilized in the Johnson, Zeidner, and Scholarios (1990) study and C_p was not tested to see if it was positive semi-definite.

However, the Whetzel (1991) study required the use of a factor solution of the matrix C_p, defined as $C_p = V R_t^{-1} V'$. Whetzel (1991) found that C_p computed in this manner did not meet the positive semi-definite condition. Since it was apparent from previous work by Johnson, Zeidner, and Scholarios (1990) that R_t was positive semi-definite, the failure of C_p to meet this condition had to be due to the matrix V; apparently it would not be possible to obtain this particular V matrix from the analysis of a single sample of either empirical or synthetic predictor and criterion scores. A very small adjustment was all that was required to provide a V matrix that results in a C_p matrix that is positive semi-definite. Appendix E details the steps taken to remove the effects of negative roots on V.

The corrected R_t and V matrices for the 60 job samples from the "McLaughlin" data did not have the problem of negative eigenvalues. It was found that $V R_t^{-1} V'$, where V is a 18 by 9 validity matrix and R_t is a 9 by 9 matrix of correlation coefficients among the ASVAB tests, has 9 positive eigenvalues and all other eigenvalues equal to zero (i.e., with no negative roots).

Thus, $V R_t^{-1} V'$ is positive semi-definite, and both R_t and V are shown to result from data that are consistent within the predictors and across the predictor and criterion variable sets.

B. Research Design

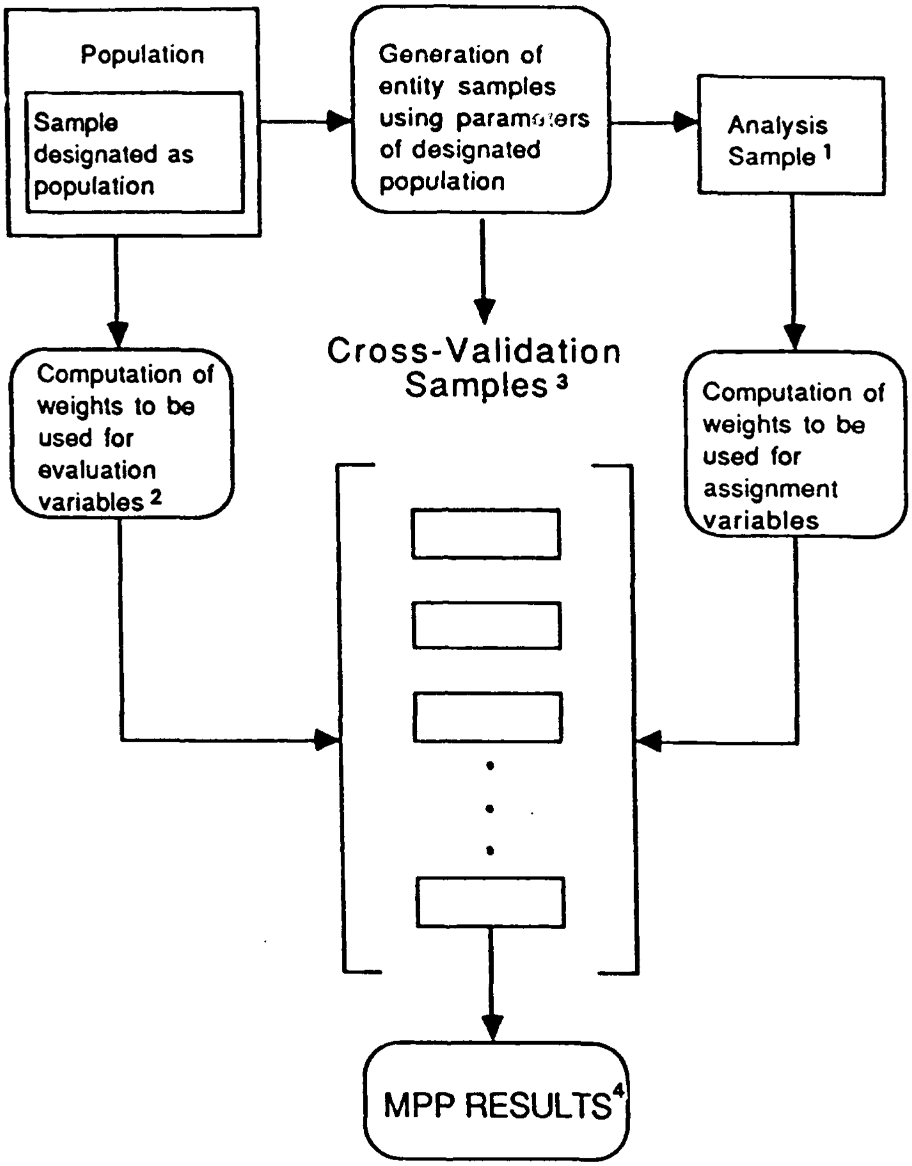
1. Cross-Validation Design

The model sampling paradigm allowed the construction of a carefully controlled, cross-validation design for this research. Figure 1 is helpful in understanding this design feature. The concept from which the cross-validation model sampling design is derived is based on the assumption that the empirical data (after corrections for criterion unreliability and restriction in range) provide a reasonable estimate of the population intercorrelations and validity coefficients used in this research. This design feature was implemented differently for Design A and Design B of this research.

For Design A, the generation of entity samples using parameters of this designated population resulted in: (1) an analysis sample and (2) cross-validation samples (see Figure 1). The analysis sample was used for job clustering and for the computation of weights to be applied to predictors in order to form composites used as assignment variables. The analysis sample was generated from random numbers that were transformed to yield test scores in independent job samples with the same sample sizes and expected covariance values among predictors and criterion as the parameters of the designated population. The algorithm for the generation of the analysis sample for Design A is given in Appendix F along with the analysis sample predictor intercorrelations (Table F-2) and the analysis sample validity coefficients (Table F-3). There were 20 cross-validation samples generated from random numbers for Design A with sample sizes of 264 entities and expected covariances equivalent to the covariances in the designated population (generation of the cross-samples is described in detail in the procedure section). Weights computed from the analysis sample are applied to the test scores of the independent cross-validation samples to compute assignment variable scores.

From Figure 1, note also that there is a third independent source used for evaluation of the assignment process. The computation of the weights to be used for the evaluation of the assignment (to compute MPP) come directly from the parameters of the designated population.

FIGURE 1: Typical Model Sampling Paradigm



[1]Job validation sample sizes equal to those used in Project A first-term concurrent validation study.

[2]Evaluation weights computed from Project A empirical sample designated as the population.

[3]Sample size of assigned entities number from 200-300; in the aggregate, N numbers in the thousands for each strategy.

[4]Predicted performance is computed using the same evaluation variable and same weights for each job across all experimental conditions.

Source: Johnson, Zeidner, and Scholarios (1990)

This cross-validation design controls two distinct sources of correlated error. A traditional source of error would occur if the validities and correlation matrices used to obtain assignment weights were based on the same sample as those used in the simulations. This traditional source of error was controlled in this experiment by having the analysis sample for computing the assignment weights independent of the 20 cross samples. A second source of error would occur if the same weights used for assigning entities to jobs were also used for evaluating this assignment. The use of the same weights for assignment and evaluation treats one type of error component as gains in true performance, thus overestimating predicted performance. For Design A, this second source of error was controlled by computing the assignment weights from the analysis sample and computing the evaluation weights directly from the designated population.

For Design B, it was not practical to create an analysis sample in the same manner as described in Appendix F because the entity sample and number of jobs was so large. For Design B, the designated population values were used in the job clustering and in the computation of assignment weights. There were 20 independent cross-validation samples that were generated with sample sizes of 400. However, note that the weights used for evaluation (from the designated population) are the same as the weights used for assignment. Thus, the first source of error described above was controlled for but the second source of error was not. Consequently, it is expected that the MPP results from Design B would be to some degree overestimates of what MPP would be if all sources of error were controlled.

Although we do not have separate analysis and evaluation samples for Design B the use of 20 independent cross-samples permits us to make the comparisons we include in Design B. All contrasts in which the correlated error between assignment and analysis variable would bias the results have been included only in Design A where this type of correlated error has been completely eliminated. We believe that the levels of the independent variables contrasted in Design B are not seriously affected by the degree and type of correlated error remaining after the traditional "back validity" type of inflation has been eliminated.

A model sampling study designed to determine the effect of various sized analysis samples have on MPP after assignment has been initiated by the first two authors of this report. This study will contrast the effect on MPP of constructing the analysis of validity (job) samples

ranging from half the size of those in the concurrent study of Project A to those several times this large. Meanwhile, the results of this study can be compared with those of Whetzel (1991) in which the analysis sample was, by implication, infinitely large.

2. Repeated Measures Design

Another special design feature used in this research is a repeated measures design. The repeated measures design chosen for this research is one in which each of the 20 cross-samples of "individuals" was exposed to all treatment conditions. This design helps to control the error variance between entities and helps to limit the number of entities that must be generated for each condition.

There are many common disadvantages associated with using a repeated measures design. However, most of these are irrelevant in the present study because this is a model sampling experiment. For example, with repeated measures it is commonly necessary to devise elaborate randomized block designs to ensure that the order of treatments do not cause confounding due to carry-over effects across conditions (e.g., from practice, fatigue, transfer of training). With an artificially generated sample of test scores this disadvantage is not an issue.

Another disadvantage often cited with repeated measures is that since the repeated measures design allows a smaller sample size, it also decreases the accuracy of estimation because the population of subjects is not as well represented as it would be if a larger sample were used. However, in this research, because it is a model sampling experiment it was possible to replicate the entire experiment 20 times thereby increasing the sample size. This replication of all conditions 20 times forms the 20 cross-samples referred to throughout this discussion. It is important that 20 cross-samples are used in this model sampling experiment instead of one large cross-sample because optimal assignment with an extremely large sample size is prohibitively expensive. Optimal assignment with smaller samples, 20 different times, is much more practical and feasible.

3. Experimental Design

This research was designed to enable an analysis of the effects of restructuring job families on classification efficiency by increasing the number of job families and by changing the composition of the jobs within these families. Design A utilized the Project A concurrent

validation data and the "McLaughlin" data for 18 jobs. Design B utilized only the "McLaughlin" data for an expanded set of 60 jobs.

Design A can be divided into three components. The first component forms the basic research design (Design A-1), with two other components forming baseline conditions based on the operational job families currently used by the U.S. Army (Designs A-2 and A-3).

a. Design A-1: Basic Research Design

The basic research design consists of three independent variables that combine to form 18 experimental conditions, each one represented by a cell containing 20 cross-samples. These three independent variables include a clustering methods factor, a number of job families factor, and a data source factor.

The clustering methods factor consists of two methods, a method for clustering jobs to maximize classification efficiency (CE method) and a method for clustering jobs to maximize selection efficiency (SE method). The CE method involves minimizing the reduction in Horst's (1954) differential index during each iteration in which jobs are formed into job families. The SE method maximizes selection efficiency by ensuring that each job family has the maximum obtainable average multiple correlation coefficient (R).

The number of job families factor consists of three levels (6, 9, and 12 families). The number of job families at each of these three levels was designed to represent the current number of operational job families, 3 less, and 3 more.

The data source variable represents three distinct sources of predictor and criterion data: (a) the experimental Project A concurrent validation test battery (Exp. Batt.-A) with the CTP criterion, (b) the standard ASVAB test battery from the Project A concurrent validation data set (ASVAB-A) with the CTP criterion, and (c) the standard ASVAB test battery from the "McLaughlin" data set (ASVAB-McL) with the SQT and training scores criteria. The experimental Project A test battery consists of the ASVAB tests plus 20 experimental predictors. This experimental test battery represents an expansion of multidimensionality in the predictor space. The experimental battery is compared to the standard ASVAB test battery from Project A to determine if expanding the predictor space results in greater MPP. The purpose of including the "McLaughlin" data set is to be able to compare the SQT/training score criteria, frequently criticized as inappropriate for personnel selection research, with the specially

developed Project A CTP criterion. Since the ASVAB-A and the ASVAB-McL conditions are both based on the same nine ASVAB tests it is possible to attribute differences in MPP between these two conditions to the different criteria measures.

Table 1 shows how the three independent variables just described combine to form the 18 experimental conditions.

Table 1

Design A-1: Basic Research Design

Clustering Methods	Job Families	Data Source		
		Exp. Batt.-A	ASVAB-A	ASVAB-McL
SE	6			
	9			
	12			
CE	6			
	9			
	12			

b. Design A-2: First Baseline Condition

The first baseline condition forms an additional design feature which is external to the above factorial design. The current U.S. Army operational nine-job-families system constitutes a baseline condition to be contrasted against a combined SE and CE, nine-job-families condition. This comparison is done for two of the three levels of the data source factor (Exp. Batt.-A and

ASVAB-A). Thus, this design will have a 2 x 2 factorial structure which requires that two new cells be created (20 cross-samples each) for the new condition. The other two cells contain data obtained from the basic research design discussed previously. Table 2 illustrates Design A-2.

Table 2

Design A-2: First Baseline Condition

	Data Source	
Clustering Methods	Exp.Batt.-A	ASVAB-A
Empirical (CE/SE)		
Operational		

The U.S. Army's job family system constitutes a baseline condition because it allows a comparison of the Army's operational job family structure to the job family structures developed empirically in this research. Note, however, that in this design all of the assignment variables are FLS composites so, although the operational job families are duplicated, the operational aptitude area composites are not. Table 3 shows the current U.S. Army operational job families and indicates which job family each of the 18 jobs included in Design A belongs.

c. Design A-3: Second Baseline Condition

The second baseline condition consists of a single condition (one cell of 20 cross-samples). In this cell, the existing U.S. Army aptitude area composites are used as assignment variables instead of FLS composites. The nine operational job families are the targets of the assignment. This condition, then, represents the current composite system that the Army uses for selection and classification. Thus, it is possible to determine the magnitude of the effects that use of the FLS composites have on MPP in comparison to the current composite system. The aptitude area composites used in this research are given in Appendix B (Table B-2). It is predicted that use of the aptitude area composites for assignment to the existing nine job families will result in the lowest MPP in comparison to any of the Project A cells in the previous two designs.

Table 3

Design A MOS Grouped into Current Operational Job Families

Operational Job Families	18 Design A MOS
Clerical/Administrative (CL)	71L Admin Specialist 76W Petroleum Supply Sp 76Y Unit Supply Sp
Combat (CO)	11B Infantryman 12B Combat Engineer 19E M49-M60 Armor Crmn
Electronics Repair (EL)	27E TOW/Dragon Repairer
Field Artillery (FA)	13B Cannon Crewman
General Maintenance (GM)	55B Ammunition Specialist
Mechanical Maintenance (MM)	63B Light Wheel Vehicle/ Power Gen Mechanic 67N Utility Helicopter Rep
Operators/Food (OF)	16S MANPADS Crewman 64C Motor Transport Op 94B Food Service Sp
Surveillance/Communication (SC)	31C Single Channel Radio Operator
Skilled Technical (ST)	54E Nuclear, Biological, and Chemical Sp 91A Medical Specialist 95B Military Police

d. Design B

Design B contains two independent variables including a clustering methods factor and a number of job families factor. In this case, the number of job families is expanded to 9, 16, and 23. This is possible due to the use of the "McLaughlin" data with 60 jobs. Table 4 illustrates the conditions of Design B.

Table 4

Design B

Job Families	Clustering Methods	
	Empirical	Operational
9		
16		
23		

The best empirical clustering method (CE or SE) is used to cluster the 60 jobs into 9, 16, and 23 job families. This clustering can then be compared to the current Army operational job families. The 9 job family operational condition represents the same 9 Army job families that were used in Design A. The 23 job family operational condition is based upon the Army's Career Management Fields (CMF). The Army currently has 33 CMF categories in which jobs are grouped, but for the present research it was only possible to include jobs from 23 of the CMF with the job sample available in the "McLaughlin" database. The 16 job family operational condition was developed for the purposes of this research as a combination of the Army's nine job family aptitude areas and the CMF. In determining these 16 job families, certain CMF categories were combined taking the 9 aptitude areas into account along with the number of jobs in the CMF categories and the similarity of the jobs in the combining categories. Thus, in several cases where a single job represented a CMF category, this job was grouped with another CMF category that contained jobs in the same aptitude area. In addition, some CMF categories were combined based on the similarities of the jobs and similarities of the aptitude areas. For example, CMF 63 Mechanical Maintenance and CMF 67 Aircraft Maintenance were combined because the jobs were all maintenance jobs that cut across the same

two aptitude areas (general mechanical and mechanical maintenance). Tables 5, 6, and 7 present the 60 jobs used in Design B grouped into the 9, 16, and 23 Army operational job families. Each table contains columns of numbers following the jobs to indicate where the jobs are grouped in the other job family structures.

C. Procedure

1. Job Clustering Procedures

Jobs were to be clustered into job families using two different clustering algorithms. One clustering algorithm attempted to maximize classification efficiency by minimizing the reduction in Horst's (1954) differential index during each iteration in which jobs are formed into job families. The second algorithm attempted to maximize selection efficiency by ensuring that each job family formed has the maximum obtainable average multiple correlation coefficient (R).

a. Clustering to Maximize Classification Efficiency (CE)

The algorithm that clusters jobs to maximize classification efficiency is called the classification-efficient (CE) clustering method. This method follows a series of iterative steps beginning with the input of an F matrix (see Appendix G for the classification-efficient program). The F matrix represents a principle components solution from the factorization of the joint predictor-criterion space, C_p, where C_p is calculated by:

$$C_p = V\,(R_t)^{-1}\,V'$$

For Design A, the resulting F matrix is either an 18 by 18 matrix (for Experimental Battery-Project A) or an 18 by 9 matrix (ASVAB-Project A and "McLaughlin"). In other words, 18 jobs (rows) by either 18 or 9 factors (columns). For Design B, the resulting F matrix is a 60 by 9 matrix (60 jobs with 9 factors).

The column means of this F matrix are then calculated and these column means are subtracted from each corresponding column element of the F matrix to form a matrix of deviations, G. Then, this G matrix is post-mulitiplied by its transpose, GG', and the diagonal elements of the resulting matrix are extracted to form a vector D_g. The weighted sum of all of the elements of this D_g vector are equal to an average H_d (Horst's differential index) across job families. For the first iteration the weights to be applied to the D_g vector will all be one, but

Table 5

Design B MOS Grouped into 9 Operational Job Families

#	MOS	n	9 APTITUDE AREA(AA)	16 COMBINED CMF	23 CMF
1. CLERICAL/ADMINISTRATIVE					
	71L Administrative Sp*	2824	1	9	13
	71M Chapel Activities Sp	182	1	9	13
	73C Finance Specialist	688	1	9	13
	75B Personnel Admin Sp	1061	1	9	13
	76C Eq Rec & Parts Sp	331	1	11	15
	76V Mat Stor & Hdlg Sp	216	1	11	15
	76Y Unit Supply Sp*	1149	1	11	15
	76W Petroleum Supply Sp*	664	1	11	16
	71N Traffic Mgmt Coordinator	163	1	12	17
2. COMBAT					
	11B Infantryman*	6355	2	1	1
	11C Indirect Fire Infmn	1494	2	1	1
	11H HV Anti-Armor Wpn Infn	979	2	1	1
	12B Combat Engineer*	3109	2	1	2
	12F Engineer Tracked Crmn	151	2	1	2
	19D Cavalry Scout	1249	2	1	5
	19E M48-M60 Armor Crmn*	3297	2	1	5
3. ELECTRONICS REPAIR					
	27E TOW/Dragon Rep*	363	3	3	6
	27F Vulcan Repairer	130	3	3	6
	31M Multichannel Comm Eq Op	2482	3	4	7
	31N Tactical Ckt Con	189	3	4	7
	31V Tac Comm Sysop/Mech	515	3	4	7
	36C Wire Sys Inst/Op	499	3	4	7
4. FIELD ARTILLERY					
	13B Cannon Crmn*	6575	4	2	3
	13F Fire Support Sp	693	4	2	3
5. GENERAL MECHANICAL					
	62E HV Const Equip Rep	202	5	5	8
	62F Lifting/Loading Eq Op	129	5	5	8
	55B Ammunition Sp*	288	5	7	10
	52D Power Generation Equip Rep	178	5	8	11
	68J Aircraft FC Repairer	148	5	8	12
	43E Parachute Rigger	100	5	11	15
	57H Cargo Specialist	272	5	12	17

(Continued)

Table 5 (Continued)

#	MOS	n	9 :APTITUDE :AREA(AA)	16 COMBINED CMF	23 CMF
6. MECHANICAL MAINTENANCE					
	12C Bridge Crewman	450	6	1	2
	62B Construction Equip Rep	233	6	8	11
	63B Lt Wh Veh/Pwr Gen Mech*	1495	6	8	11
	63H Track Veh Repairer	335	6	8	11
	63N M60A1/A3 Tank Sys Mech	286	6	8	11
	63W Wheel Veh Mechanic	180	6	8	11
	67N Utility Hel Repairer*	511	6	8	12
	67V OBN/Scout Hel Rep	294	6	8	12
	68G Aircraft Structural Rep	125	6	8	12
7. OPERATORS/FOOD					
	15D Lance Crmb/MLRS Sgt	281	7	2	3
	16S MANPADS Crewmember*	596	7	2	4
	64C Motor Transport Op*	3681	7	12	17
	94B Food Service Sp*	3943	7	15	20
8. SURVEILLANCE/COMMUNICATION					
	05C Radio TT Operator*	2393	8	4	7
	72E Combat Telecom Center Op	569	8	4	7
9. SKILLED TECHNICAL					
	13E Cannon Fire Direction Sp	627	9	2	3
	82C Field Artillery Surveyor	434	9	2	3
	54E NBC Specialist*	113	9	6	9
	74D Computer/Tape Writer	132	9	10	14
	74F Programmer/Analyst	95	9	10	14
	91B Medical Specialist*	783	9	13	18
	91E Dental Specialist	203	9	13	18
	91P X-Ray Specialist	159	9	13	18
	92B Medical Lab Sp	310	9	13	18
	93H Air Traffic Con Tower Op	114	9	14	19
	95B Military Police*	4516	9	16	21
	96B Intelligence Analyst	218	9	16	22
	05H Elec War/SIGINT INTER_IMC	171	9	16	23
	98C Elec War/SIGINT Analyst	186	9	16	23

* = MOS for Design A

Table 6

Design B MOS Grouped into 16 Operational Job Families

#	MOS	n	9 APTITUDE AREA(AA)	16 COMBINED CMF	23 CMF
Job Family 1					
	11B Infantryman*	6355	2	1	1
	11C Indirect Fire Infmn	1494	2	1	1
	11H HV Anti-Armor Wpn Infn	979	2	1	1
	12B Combat Engineer*	3109	2	1	2
	12F Engineer Tracked Crmn	151	2	1	2
	19D Cavalry Scout	1249	2	1	5
	19E M48-M60 Armor Crmn*	3297	2	1	5
	12C Bridge Crewman	450	6	1	2
Job Family 2					
	13B Cannon Crmn*	6575	4	2	3
	13F Fire Support Sp	693	4	2	3
	15D Lance Crmb/MLRS Sgt	281	7	2	3
	16S MANPADS Crewmember*	596	7	2	4
	13E Cannon Fire Direction Sp	627	9	2	3
	82C Field Artillery Surveyor	434	9	2	3
Job Family 3					
	27E TOW/Dragon Rep*	363	3	3	6
	27F Vulcan Repairer	130	3	3	6
Job Family 4					
	31M Multichannel Comm Eq Op	2482	3	4	7
	31N Tactical Ckt Con	189	3	4	7
	31V Tac Comm Sysop/Mech	515	3	4	7
	36C Wire Sys Inst/Op	499	3	4	7
	05C Radio TT Operator*	2393	8	4	7
	72E Combat Telecom Center Op	569	8	4	7
Job Family 5					
	62E HV Const Equip Rep	202	5	5	8
	62F Lifting/Loading Eq Op	129	5	5	8
Job Family 6					
	54E NBC Specialist*	113	9	6	9
Job Family 7					
	55B Ammunition Sp*	288	5	7	10
Job Family 8					
	52D Power Generation Equip Rep	178	5	8	11
	68J Aircraft FC Repairer	148	5	8	12
	62B Construction Equip Rep	233	6	8	11
	63B Lt Wh Veh/Pwr Gen Mech*	1495	6	8	11
	63H Track Veh Repairer	335	6	8	11
	63N M60A1/A3 Tank Sys Mech	286	6	8	11
	63W Wheel Veh Mechanic	180	6	8	11
	67N Utility Hel Repairer*	511	6	8	12
	67V OBN/Scout Hel Rep	294	6	8	12
	68G Aircraft Structural Rep	125	6	8	12

(Continued)

Table 6 (Continued)

#	MOS	n	9 :APTITUDE :AREA(AA)	16 COMBINED CMF	23 CMF
Job Family 9					
	71L Administrative Sp*	2824	1	9	13
	71M Chapel Activities Sp	182	1	9	13
	73C Finance Specialist	688	1	9	13
	75B Personnel Admin Sp	1061	1	9	13
Job Family 10					
	74D Computer/Tape Writer	132	9	10	14
	74F Programmer/Analyst	95	9	10	14
Job Family 11					
	76C Eq Rec & Parts Sp	331	1	11	15
	76V Mat Stor & Hdlg Sp	216	1	11	15
	76Y Unit Supply Sp*	1149	1	11	15
	76W Petroleum Supply Sp*	664	1	11	16
	43E Parachute Rigger	100	5	11	15
Job Family 12					
	71N Traffic Mgmt Coordinator	163	1	12	17
	57H Cargo Specialist	272	5	12	17
	64C Motor Transport Op*	3681	7	12	17
Job Family 13					
	91B Medical Specialist*	783	9	13	18
	91E Dental Specialist	203	9	13	18
	91P X-Ray Specialist	159	9	13	18
	92B Medical Lab Sp	310	9	13	18
Job Family 14					
	93H Air Traffic Con Tower Op	114	9	14	19
Job Family 15					
	94B Food Service Sp*	3943	7	15	20
Job Family 16					
	95B Military Police*	4516	9	16	21
	96B Intelligence Analyst	218	9	16	22
	05H Elec War/SIGINT INTER_IMC	171	9	16	23
	98C Elec War/SIGINT Analyst	186	9	16	23

* = MOS for Design A

Table 7

Design B MOS Grouped into 23 Operational Job Families

#	MOS	n	9 :APTITUDE :AREA(AA)	16 COMBINED CMF	23 CMF
1. INFANTRY (11)					
	11B Infantryman*	6355	2	1	1
	11C Indirect Fire Infmn	1494	2	1	1
	11H HV Anti-Armor Wpn Infn	979	2	1	1
2. COMBAT ENGINEERING (12)					
	12B Combat Engineer*	3109	2	1	2
	12F Engineer Tracked Crmn	151	2	1	2
	12C Bridge Crewman	450	6	1	2
3. FIELD ARTILLERY (13)					
	13B Cannon Crmn*	6575	4	2	3
	13F Fire Support Sp	693	4	2	3
	15D Lance Crmb/MLRS Sgt	281	7	2	3
	13E Cannon Fire Direction Sp	627	9	2	3
	82C Field Artillery Surveyor	434	9	2	3
4. AIR DEFENSE ARTILLERY (16)					
	16S MANPADS Crewmember*	596	7	2	4
5. ARMOR (19)					
	19D Cavalry Scout	1249	2	1	5
	19E M48-M60 Armor Crmn*	3297	2	1	5
6. LAND COMBAT/AD SYS INTRM MAINTENANCE (27)					
	27E TOW/Dragon Rep*	363	3	3	6
	27F Vulcan Repairer	130	3	3	6
7. SIGNAL OPERATIONS (31)					
	31M Multichannel Comm Eq Op	2482	3	4	7
	31N Tactical Ckt Con	189	3	4	7
	31V Tac Comm Sysop/Mech	515	3	4	7
	36C Wire Sys Inst/Op	499	3	4	7
	05C Radio TT Operator*	2393	8	4	7
	72E Combat Telecom Center Op	569	8	4	7
8. GENERAL ENGINEERING (51)					
	62E HV Const Equip Rep	202	5	5	8
	62F Lifting/Loading Eq Op	129	5	5	8
9. CHEMICAL (54)					
	54E NBC Specialist*	113	9	6	9
10. AMMUNITION (55)					
	55B Ammunition Sp*	288	5	7	10
11. MECHANICAL MAINTENANCE (63)					
	52D Power Generation Equip Rep	178	5	8	11
	62B Construction Equip Rep	233	6	8	11
	63B Lt Wh Veh/Pwr Gen Mech*	1495	6	8	11
	63H Track Veh Repairer	335	6	8	11
	63N M60A1/A3 Tank Sys Mech	286	6	8	11
	63W Wheel Veh Mechanic	180	6	8	11

(Continued)

Table 7 (Continued)

#	MOS	n	9 :APTITUDE :AREA(AA)	16 COMBINED CMF	23 CMF
12.	AIRCRAFT MAINTENANCE (67)				
	68J Aircraft FC Repairer	148	5	8	12
	67N Utility Hel Repairer*	511	6	8	12
	67V OBN/Scout Hel Rep	294	6	8	12
	68G Aircraft Structural Rep	125	6	8	12
13.	ADMINISTRATION (71)				
	71L Administrative Sp*	2824	1	9	13
	71M Chapel Activities Sp	182	1	9	13
	73C Finance Specialist	688	1	9	13
	75B Personnel Admin Sp	1061	1	9	13
14.	AUTOMATIC DATA PROCESSING (74)				
	74D Computer/Tape Writer	132	9	10	14
	74F Programmer/Analyst	95	9	10	14
15.	SUPPLY AND SERVICE (76)				
	76C Eq Rec & Parts Sp	331	1	11	15
	76V Mat Stor & Hdlg Sp	216	1	11	15
	76Y Unit Supply Sp*	1149	1	11	15
	43E Parachute Rigger	100	5	11	15
16.	PETROLEUM AND WATER (77)				
	76W Petroleum Supply Sp*	664	1	11	16
17.	TRANSPORTATION (88)				
	71N Traffic Mgmt Coordinator	163	1	12	17
	57H Cargo Specialist	272	5	12	17
	64C Motor Transport Op*	3681	7	12	17
18.	MEDICAL (91)				
	91B Medical Specialist*	783	9	13	18
	91E Dental Specialist	203	9	13	18
	91P X-Ray Specialist	159	9	13	18
	92B Medical Lab Sp	310	9	13	18
19.	AVIATION OPERATION				
	93H Air Traffic Con Tower Op	114	9	14	19
20.	FOOD SERVICE (94)				
	94B Food Service Sp*	3943	7	15	20
21.	MILITARY POLICE (96)				
	95B Military Police*	4516	9	16	21
22.	MILITARY INTELLIGENCE (96)				
	96B Intelligence Analyst	218	9	16	22
23.	ELECTRONIC WARFARE/CRYPTOLOGIC OP (98)				
	05H Elec War/SIGINT INTER_IMC	171	9	16	23
	98C Elec War/SIGINT Analyst	186	9	16	23

* = MOS for Design A

as jobs are formed into job families, the weights become equal to the number of jobs in each developing job family. This process ensures that average H_d will always correspond to all of the jobs in the evolving job families.

The next step in this algorithm utilizes the D_g vector to form an A matrix. This A matrix consists of the weighted sum of all possible combinations of the elements of the D_g vector. Each element of the A matrix is calculated using the following formula:

$$a_{ij} = n_i(d_i) + n_j(d_j)$$

where,

d = an element of D_g
n = number of jobs in the ith or jth job family

Thus, the A matrix is a m by m square matrix, where m is the number of job families. Conceptually, the A matrix represents the contribution of the jobs in each pair of evolving job families to H_d.

The next step in this algorithm utilizes the F matrix described previously to form a B matrix. For each column of F, the ith and jth factor loadings are summed, weighted by n_i and n_j to form the weighted sums. These sums are divided by $(n_i + n_j)$. The column mean is then subtracted and each difference is squared. These calculations are repeated for each column of F and all of these elements are summed and mulitiplied by $(n_i + n_j)$ to form the ith and jth elements of the B matrix. This process is repeated for all possible combinations of elements in the F matrix. The notation for these calculations can be represented as follows:

$$\begin{aligned} B_{ij} = {} & [(((n_i f_{i1} + n_j f_{j1})/(n_i + n_j)) - c_1)^2 + \\ & (((n_i f_{i2} + n_j f_{j2})/(n_i + n_j)) - c_2)^2 + \\ & \ldots \; (((n_i f_{im} + n_j f_{jm})/(n_i + n_j)) - c_m)^2](n_i + n_j) \end{aligned}$$

where,

f = an element of the F matrix
n = number of jobs in the ith or jth job family
c = column means from the F matrix
m = number of job families

Conceptually, the B matrix acts as a trial deviation matrix that indicates how much of a reduction in H_d there is when any two job families for that iteration are combined.

The final step in the algorithm is to subtract all of the elements in the B matrix from all of the elements in the A matrix (i.e., A - B) to form a D matrix. The smallest element in this D matrix represents the two jobs (or job families) that when combined will minimize the reduction in H_d. Thus, the two job families corresponding to the smallest value in the D matrix are chosen and the two rows representing these job families in the F matrix are averaged together to form a new F matrix. This new, smaller F matrix is then used to begin the next iteration. It is important to note that the same column means of the F matrix from the very first iteration (i.e., all jobs) are used for every iteration. Thus, each new iteration starts, not with the recalculation of the column means, but with the recalculation of the G matrix.

Depending upon the condition, the number of iterations continues until either 6, 9, or 12 job families are formed in Design A and until 9, 16, or 23 job families are formed in Design B. H_d is calculated during each iteration from the D_g vector so that it is possible to track the amount it is reduced with each iteration.

b. Clustering to Maximize Selection Efficiency (SE)

The algorithm that clusters jobs to maximize predictive validity is called the selection-efficient (SE) clustering method. This algorithm represents a heuristic that attempts to provide a practical way of obtaining the highest possible predictive validity in a set of job clusters. The absolute optimal method for forming selection-efficient job clusters would be to evaluate every possible combination of jobs in terms of predictive validity. This would require calculating R^2 values for millions of different combinations which is beyond the practical resources for this research. Instead, an algorithm was developed that utilizes two stages in an attempt to obtain the highest predictive validity possible (see Appendix H for the selection-efficient clustering program). The descriptions contained in this section are limited to describing the selection-efficient procedures for clustering the 18 jobs in Design A. This clustering procedure was not used in Design B.

In the first stage, the validity matrix (V) from the analysis sample is used to determine an initial combination of jobs into job families. Each row of V represents the validities pertaining to a job. Depending upon the condition (6, 9, or 12 job families), differing numbers of rows are averaged to form single validity vectors. For example, for the 6 job family condition, all possible combinations (816 combinations) of three jobs are averaged. The result

is a new 816 x 29 validity matrix (V_1) in which each row represents a different three-job combination. For each of these rows, $V(R_t)^{-1}V'$ is calculated to obtain R^2 (R_t is the matrix of predictor intercorrelations from the analysis sample). An iterative procedure is then performed in which the three-job group with the largest R is selected first, then the next largest R that does not involve the three jobs in the first selected family, etc. until six non-overlapping families have been located. Thus, for the 6 job families condition, all 18 jobs are covered by the six groupings of three jobs each. For the 9 job families condition, all possible combinations (153 combinations) of two jobs will be averaged forming V_2 and then the iteration procedure described above commences. For the 12 job families condition, as many two job combinations as possible will be formed, but some of the final job groupings will contain only one job (V_3).

In the second stage, the initial job groupings formed in the first stage are shredded to determine if other job combinations result in higher average multiple R's. For example, for the 6 job family condition, beginning with the triplet with the lowest average R, each job in that triplet will be considered with every other grouping and a new average R calculated using the formula: $tr[V(R_t)^{-1}V'](1/m)$. Of these 15 trials, the trial combination with the greatest overall average R will be selected. This shredding process will be repeated with the next set of triplets (and eventually sets of doubles) until no substantial increase in average R is obtained. However, note that for each of the conditions there must always be at least one job in each of the job families. In addition, once a job cluster has had other jobs added to it, that job cluster no longer becomes eligible to be shredded. This job cluster does continue to be eligible to have jobs added to it.

In this way, selection-efficient job family clusters are created. The composition of the job family clusters will differ depending upon whether there are 6, 9, or 12 job families. Note also that the composition of the clusters will differ depending upon the data source.

2. Cross-Sample Generation of Synthetic Scores

For this research, 20 cross-samples were generated using model sampling techniques for both Designs A and B. The goal in generating these cross-samples is to obtain predicted performance scores (LSEs) for all entities in every job family. The procedure for accomplishing this generation involves four stages which are discussed below:

a. the generation of random normal deviates;

b. the transformation of normal deviates into test scores simulating the characteristics of the test scores in the designated population;

c. the transformation of test scores into predicted performance scores corresponding to each job family for use as assignment variables;

d. elimination of all performance scores below a cutting score on the AFQT which eliminates 25% of all generated entities (to simulate selection).

a. Generation of Random Normal Deviates

In the first stage, a uniformly distributed random sequence of numbers ranging from 0 to 1, with an approximate mean of 0.5 and a variance of 0.0833 was produced using a pseudo-random number generator (Appendix I contains the program for the random number generator). The choice of a random number generator routine was based on evidence documenting efficient imple:nentation and empirical tests of the randomness of the program's output (Park & Miller, 1988). A clearly defined algorithm, initial parameters, and a recorded initial seed allow replication of the experiment (see Appendix I, Tables I-1 and I-2 for the initialization seeds used for this study). The optimal multipliers for producing the number sequence were based on Fishman and Moore's (1986) recommendations. Thus, the potential problems inherent in a random number generator are minimized by careful selection of routines and inputs.

The sequence of uniformly distributed random numbers was transformed into a distribution of normal variables by calculating the expected mean and dividing by expected values to give a mean of 0 and standard deviation of 1.0. These calculations produced a matrix of normal deviates, X_n, of order N by n, where N is the number of entities (individuals) and n is the number of simulated scores representing the full set predictors. For Design A, one sample of N=264 and n=29 was generated for each of twenty separate cross-samples. For Design B, one sample of N=400 and n=9 was generated for each of twenty separate cross-samples.

b. Transformation of Random Normal Deviates to Test Scores

The aim at this second stage was to transform the matrix X_n into a matrix of test scores (Y) for each of the experimental conditions. The generated test scores are required to have expected covariances equivalent to those of the population which are represented by the intercorrelations in R_t, i.e., $E(1/N(Y'Y)) = R_t$. A Gramian factor solution ($F_t = AD^{1/2}A'$,

where A and D are the eigenvectors and eigenvalues of the population predictor intercorrelations, respectively), was used to transform the matrix X_n into a matrix of test scores (Y). Thus, Y was generated by $Y = X_n F_t$. In Design A, for the "McLaughlin" and Project A-ASVAB conditions, only the first nine test scores (corresponding to the nine ASVAB tests) are retained for the next stage.

c. Transformation of Test Scores to FLS Composites

The aim in this third stage was to generate an N by m matrix (Z) of predicted performance scores to be used as assignment variables, where N is the number of entities and m is the number of jobs. Thus, this Z matrix contained the predicted performance of each entity in every job family. A transformation matrix of beta weights, $W = R_t^{-1}V'$, was computed using the analysis sample data (for Design B the population data was utilized). A different V matrix was used in each of the 18 conditions because each condition represents a different set of job families. The weights are applied to the Y matrices of cross-samples so that the calculation of predicted performance scores is accomplished by $Z = YW$.

d. Selection of Entities by the AFQT Score

Within each sample, a selection ratio of 0.75 was applied based upon a ranking on synthetic AFQT scores. Thus, entities with the lowest 25% of the AFQT scores were dropped from the analysis and not considered for assignment. For each cross-sample in Design A, out of the 264 entities generated, 198 entities were optimally assigned. For Design B, out of the 400 entities generated, 300 entities were optimally assigned. The AFQT score is calculated by the formula containing the ASVAB tests Arithmetic Reasoning, Numerical Operations, and Verbal Ability (Appendix B, Table B-2). Note that the Army's computation of the AFQT has recently been modified to included Mathematical Knowledge instead of the weighted Numerical Operations test (see Welsh, Kucinkas, & Curran, 1990). The original equation will be used in this study to coincide with the time-frame of the Project A concurrent validation and "McLaughlin" data collections.

3. Assignment Simulation

Entities are optimally assigned to job families through the use of a hybrid adaptation of a primal linear programming (simplex) algorithm. The optimal assignment procedure is a modified personal computer version of the "NETG" mathematical programming system

(published by Analysis, Research, and Computation, Inc., Austin, Texas). It is implemented through the use of a circularized network optimization model. In this assignment algorithm, quotas are met at each iteration while the allocation sum converges toward the final optimal solution. At the final iteration the objective function, MPP, based on evaluation sample weights, is maximized.

For this study, entities are optimally assigned to job families not individual jobs. Once assignment to a job family has occurred the entities are randomly assigned to the jobs within that job family as a second assignment stage. The quotas for job families are set so that there will be equal quotas for each job in every condition. For Design A, since there were 18 jobs, equal quotas of 11 entities per job were set so that all 198 selected entities were assigned. For Design B, since there were 60 jobs, equal quotas of 5 entities per job were set so that all 300 selected entities were assigned. Note that the actual number of entities assigned to each job family as a constraint of the optimal assignment algorithm will differ depending upon how many jobs are in that family.

For all of the designs in this research except Design A-3, the assignment variables are FLS composites. For Design A-3, U.S. Army aptitude area composites were calculated for use as assignment variables. After assignment, regression weights derived from the designated population (the evaluation weights) are used to calculate the MPP of entities in each job. Assignment is made by job family, but evaluation using MPP based on weights obtained from the population, is accomplished separately for each job.

III. EXPECTED FINDINGS AND ACTUAL RESULTS

A MPP standard score represents the average of expected performance for a sample of entities on the jobs to which each is assigned. The procedure described above produced 20 MPP scores for each condition in Designs A and B. The expected findings for Designs A and B are described separately below.

Design A

1. **Number of Job Families**

a. The magnitude of the MPP scores will increase significantly as the number of job families is increased from 6 to 9 and then to 12 job families.

b. The efficiency of classification varies with the number of job families according to a negatively accelerated function such that the increase in MPP from 6 to 9 job families will be greater than the increase in MPP from 9 to 12 job families.

2. **Job Clustering Methods**

a. The CE clustering method will result in significantly greater MPP scores than the SE clustering method across all conditions.

b. The empirical methods of job clustering (CE and SE) will result in significantly greater MPP scores than the current U.S. Army operational job families.

c. Clustering based on all 29 Project A tests will provide significantly greater MPP than clustering based on the standard 9 ASVAB tests.

3. **Type of Predictor Measure**

When the assignment variables are based on all 29 Project A tests, MPP will be significantly greater than when the assignment variables are based on the standard 9 ASVAB tests.

4. **Type of Criterion Measure**

a. There will be no significant difference in MPP scores due to the use of assignment variables based on the Project A concurrent validation criterion measure, Core Technical

Proficiency, and the "McLaughlin" 1981-1982 criterion measures, Skill Qualification Tests (SQTs) and end-of-course training scores.

b. The conclusions from statistical significance tests between the levels of all of the other variables in this design will be the same when either set of data (differing with respect to the two kinds of criteria) is used to: (1) select job family sets, and (2) compute weights to be applied to assignment variables. If the conclusions reached using the two different criteria for hypotheses 1 and 2 are the same, then this hypothesis is accepted. If any significance test has different results for the two criteria, the p-values will be examined to determine if they are within a designated range (i.e., .10) indicating that for practical purposes conclusions using the two criteria are essentially the same.

5. **FLS Composites versus Aptitude Area Composites**

Any condition involving FLS assignment will result in significantly greater MPP scores than assignment based upon the Army operational aptitude area composites.

<u>Design B</u>

1. **Number of Job Families**

a. The magnitude of the MPP scores will increase significantly as the number of job families is increased from 9 to 16 and then to 23 job families.

b. The efficiency of classification varies with the number of job families according to a negatively accelerated function such that the increase in MPP from 9 to 16 job families will be greater than the increase in MPP from 16 to 23 job families.

2. **Job Clustering Methods**

a. The empirical methods of job clustering (CE and SE) will result in significantly greater MPP scores than the current U.S. Army aptitude area job families, the Career Management Field (CMF) categories, or a combination of these two operational groupings.

A. Job Clustering Results

The classification-efficient (CE) clustering method was successful in providing job clusters that minimized the reduction in Horst's differential index, H_d, during each iteration. The selection-efficient (SE) clustering method, however, was not successful in creating job clusters that maximized predictive validity. Nevertheless, it was discovered that the CE clusters actually had very high average weighted R^2 values even though these jobs were clustered based

on H_d. Explanations for the lack of success with the SE method as well as further implications are discussed below. Also discussed below is a comparison of the operational job families to the empirical job families in terms of several key indices.

1. Classification-Efficient Job Families

The classification-efficient clustering method resulted in sets of 6, 9, and 12 job families for Design A and sets of 9, 16, and 23 job families for Design B. For Design A, 18 jobs were clustered into job families using three different data sources (Project A--Experimental Battery; Project A--ASVAB; and "McLaughlin"). Tables 8, 9, and 10 present the classification-efficient job families for each data source in Design A. For Design B, 60 jobs from the "McLaughlin" database were clustered into job families. Tables 11, 12, and 13 present the classification-efficient job families for Design B.

Corresponding to each of these sets of job families is a value for Horst's average differential index, H_d/m, where m is the number of assignment variables (i.e., job families). Table 14 presents the H_d/m indices for all conditions. As expected, there were increases in the H_d indices as the number of job families increased from 6 to 9 to 12, and from 9 to 16 to 23. This finding gives an indication of the amount of differential validity gained in the "back" sample as the number of job families is increased.

Johnson and Zeidner (1990, 1991) criticized the use of a version of H_d proposed by McLaughlin et al. (1984) as a measure of CE. McLaughlin et al. (1984) proposed use of an index, M, as a measure of CE when the assignment variables are not FLS composites. The use of M cannot be justified as comparable to Horst's index of differential validity (H_d) and was inappropriate for use as a measure of CE. However, McLaughlin et al. (1984) proposed a baseline measure, H, which appears to be proportional to H_d ($H^2 = H_d/m$). The index H would be proportional to H_d across data sets. The use of H_d in the "back" (analysis) sample as an approximation of CE is comparable to the use of H, but not M, in McLaughlin et al. (1984) as a measure of CE.

Also included in Table 14 is a ceiling average H_d value which is the maximum amount of H_d/m possible in a set of data determined by calculating H_d for all jobs prior to clustering. The purpose of the CE clustering method was to minimize the reduction in H_d as jobs are formed into job families. Comparisons with the ceiling values give an indication of the

Table 8

Design A Classification-Efficient Job Families for Project A (Experimental Battery)

Datà Source

6 Job Families	9 Job Families	12 Job Families
Job Family 1 Infantryman NBC Specialist Petroleum Supply Specialist Combat Engineer M48-M60 Armor Crewmember	Job Family 1 Infantryman NBC Specialist Petroleum Supply Specialist Combat Engineer M48-M60 Armor Crewmember	Job Family 1 Infantryman NBC Specialist Petroleum Supply Specialist
Job Family 2 Cannon Crewmember Light Wheel Vehicle Mechanic Medical Specialist Motor Transport Operator Military Police Utility Helicopter Repairer	Job Family 2 Cannon Crewmember Light Wheel Vehicle Mechanic Medical Specialist	Job Family 2 Combat Engineer M48-M60 Armor Crewmember
Job Family 3 MANPADS Crewmember Administrative Specialist Food Service Specialist Unit Supply Specialist	Job Family 3 MANPADS Crewmember	Job Family 3 Cannon Crewmember
Job Family 4 TOW/DRAGON Repairer	Job Family 4 TOW/DRAGON Repairer	Job Family 4 MANPADS Crewmember
Job Family 5 Single Channel Radio Operator	Job Family 5 Single Channel Radio Operator	Job Family 5 TOW/DRAGON Repairer
Job Family 6 Ammunition Specialist	Job Family 6 Ammunition Specialist	Job Family 6 Single Channel Radio Operator
	Job Family 7 Motor Transport Operator Military Police Utility Helicopter Repairer	Job Family 7 Ammunition Specialist
	Job Family 8 Administrative Specialist Food Service Specialist	Job Family 8 Light Wheel Vehicle Mechanic Medical Specialist
	Job Family 9 Unit Supply Specialist	Job Family 9 Motor Transport Operator Military Police
		Job Family 10 Utility Helicopter Repairer
		Job Family 11 Administrative Specialist Food Service Specialist
		Job Family 12 Unit Supply Specialist

Table 9

Design A Classification-Efficient Job Families for Project A (ASVAB tests)

Data Source

6 Job Families

Job Family 1
Infantryman
Unit Supply Specialist
NBC Specialist
Single Channel Radio Operator

Job Family 2
Combat Engineer
M48-M60 Armor Crewmember
TOW/DRAGON Repairer

Job Family 3
Cannon Crewmember
Light Wheel Vehicle Mechanic
Utility Helicopter Repairer
Motor Transport Operator

Job Family 4
MANPADS Crewmember
Medical Specialist
Military Police

Job Family 5
Ammunition Specialist
Administrative Specialist
Food Service Specialist

Job Family 6
Petroleum Supply Specialist

9 Job Families

Job Family 1
Infantryman
Unit Supply Specialist
NBC Specialist

Job Family 2
Combat Engineer
M48-M60 Armor Crewmember
TOW/DRAGON Repairer

Job Family 3
Cannon Crewmember
Light Wheel Vehicle Mechanic
Utility Helicopter Repairer

Job Family 4
MANPADS Crewmember
Medical Specialist
Military Police

Job Family 5
Single Channel Radio Operator

Job Family 6
Ammunition Specialist

Job Family 7
Motor Transport Operator

Job Family 8
Administrative Specialist
Food Service Specialist

Job Family 9
Petroleum Supply Specialist

12 Job Families

Job Family 1
Infantryman
Unit Supply Specialist
NBC Specialist

Job Family 2
Combat Engineer
M48-M60 Armor Crewmember

Job Family 3
Cannon Crewmember
Light Wheel Vehicle Mechanic
Utility Helicopter Repairer

Job Family 4
MANPADS Crewmember
Medical Specialist

Job Family 5
TOW/DRAGON Repairer

Job Family 6
Single Channel Radio Operator

Job Family 7
Ammunition Specialist

Job Family 8
Motor Transport Operator

Job Family 9
Administrative Specialist

Job Family 10
Petroleum Supply Specialist

Job Family 11
Food Service Specialist

Job Family 12
Military Police

Table 10

Design A Classification-Efficient Job Families for McLaughlin Data Source

6 Job Families

Job Family 1
Single Channel Radio Operator
Motor Transport Operator
M48-M60 Armor Crewmember
Food Service Specialist
Military Police
Infantryman
Cannon Crewmember

Job Family 2
Combat Engineer
Light Wheel Vehicle Mechanic
Utility Helicopter Repairer
Petroleum Supply Specialist
MANPADS Crewmember

Job Family 3
TOW/DRAGON Repairer

Job Family 4
NBC Specialist

Job Family 5
Ammunition Specialist
Unit Supply Specialist
Administrative Specialist

Job Family 6
Medical Specialist

9 Job Families

Job Family 1
Single Channel Radio Operator
Motor Transport Operator
M48-M60 Armor Crewmember
Food Service Specialist
Military Police

Job Family 2
Infantryman
Cannon Crewmember

Job Family 3
Combat Engineer
Light Wheel Vehicle Mechanic
Utility Helicopter Repairer
Petroleum Supply Specialist

Job Family 4
MANPADS Crewmember

Job Family 5
TOW/DRAGON Repairer

Job Family 6
NBC Specialist

Job Family 7
Ammunition Specialist
Unit Supply Specialist

Job Family 8
Administrative Specialist

Job Family 9
Medical Specialist

12 Job Families

Job Family 1
Single Channel Radio Operator
Motor Transport Operator

Job Family 2
Infantryman
Cannon Crewmember

Job Family 3
Combat Engineer
Light Wheel Vehicle Mechanic

Job Family 4
MANPADS Crewmember

Job Family 5
M48-M60 Armor Crewmember
Food Service Specialist
Military Police

Job Family 6
TOW/DRAGON Repairer

Job Family 7
NBC Specialist

Job Family 8
Ammunition Specialist
Unit Supply Specialist

Job Family 9
Utility Helicopter Repairer

Job Family 10
Administrative Specialist

Job Family 11
Petroleum Supply Specialist

Job Family 12
Medical Specialist

Table 11

Nine Classification-Efficient Job Families for Design B

JOB FAMILY	MOS	n
1	05C Radio TT Operator *	2393
1	11B Infantryman *	6355
1	11C Indirect Fire Infmn	1494
1	12B Combat Engineer *	3109
1	12C Bridge Crewman	450
1	13B Cannon Crmn *	6575
1	13F Fire Support Sp	693
1	15D Lance Crmb/MLRS Sgt	281
1	16S MANPADS Crewmember *	596
1	19D Cavalry Scout	1249
1	19E M48-M60 Armor Crmn *	3297
1	31M Multichannel Comm Eq Op	2482
1	31V Tac Comm Sysop/Mech	515
1	62B Construction Equip Rep	233
1	62E HV Const Equip Rep	202
1	63B Lt Wh Veh/Pwr Gen Mech *	1495
1	63H Track Veh Repairer	335
1	64C Motor Transport Op *	3681
1	67N Utility Hel Repairer*	511
1	67V OBN/Scout Hel Rep	294
1	72E Combat Telecom Center Op	569
1	76W Petroleum Supply Sp *	664
1	82C Field Artillery Surveyor	434
1	94B Food Service Sp *	3943
1	95B Military Police *	4516
2	05H Elec War/SIGINT INTER_IMC	171
2	98C Elec War/SIGINT Analyst	186
3	11H HV Anti-Armor Wpn Infn	979
3	13E Cannon Fire Direction Sp	627
3	27E TOW/Dragon Rep *	363
3	31N Tactical Ckt Con	189
3	55B Ammunition Sp *	288
3	76Y Unit Supply Sp *	1149
3	91E Dental Specialist	203
3	91P X-Ray Specialist	159
3	92B Medical Lab Sp	310
4	12F Engineer Tracked Crmn	151
4	36C Wire Sys Inst/Op	499
4	63N M60A1/A3 Tank Sys Mech	286
4	63W Wheel Veh Mechanic	180
4	68J Aircraft FC Repairer	148
4	91B Medical Specialist *	783
5	27F Vulcan Repairer	130
5	52D Power Generation Equip Rep	178
5	54E NBC Specialist *	113
6	43E Parachute Rigger	100
6	68G Aircraft Structural Rep	125
6	76C Eq Rec & Parts Sp	331
7	57H Cargo Specialist	272
7	71N Traffic Mgmt Coordinator	163
8	62F Lifting/Loading Eq Op	129
8	71M Chapel Activities Sp	182
8	74F Programmer/Analyst	95
9	71L Administrative Sp *	2824
9	73C Finance Specialist	688
9	74D Computer/Tape Writer	132
9	75B Personnel Admin Sp	1061
9	76V Mat Stor & Hdlg Sp	216
9	93H Air Traffic Con Tower Op	114
9	96B Intelligence Analyst	218

* = MOS for Design A

(continued)

Table 12

Sixteen Classification-Efficient Job Families for Design B

JOB FAMILY	MOS	n
1	05C Radio TT Operator *	2393
1	11B Infantryman *	6355
1	11C Indirect Fire Infmn	1494
1	12C Bridge Crewman	450
1	13B Cannon Crmn *	6575
1	13F Fire Support Sp	693
1	19D Cavalry Scout	1249
1	19E M48-M60 Armor Crmn *	3297
1	31V Tac Comm Sysop/Mech	515
1	62B Construction Equip Rep	233
1	62E HV Const Equip Rep	202
1	63H Track Veh Repairer	335
1	64C Motor Transport Op *	3681
1	67V OBN/Scout Hel Rep	294
1	82C Field Artillery Surveyor	434
1	94B Food Service Sp *	3943
1	95B Military Police *	4516
2	05H Elec War/SIGINT INTER_IMC	171
2	98C Elec War/SIGINT Analyst	186
3	11H HV Anti-Armor Wpn Infn	979
3	13E Cannon Fire Direction Sp	627
3	55B Ammunition Sp *	288
3	76Y Unit Supply Sp *	1149
3	91E Dental Specialist	203
4	12B Combat Engineer *	3109
4	15D Lance Crmb/MLRS Sgt	281
4	63B Lt Wh Veh/Pwr Gen Mech *	1495
4	67N Utility Hel Repairer*	511
4	76W Petroleum Supply Sp *	664
5	12F Engineer Tracked Crmn	151
5	63W Wheel Veh Mechanic	180
6	16S MANPADS Crewmember *	596
6	31M Multichannel Comm Eq Op	2482
6	72E Combat Telecom Center Op	569
7	27E TOW/Dragon Rep *	363
7	92B Medical Lab Sp	310
8	27F Vulcan Repairer	130
8	52D Power Generation Equip Rep	178
8	54E NBC Specialist *	113
9	31N Tactical Ckt Con	189
9	91P X-Ray Specialist	159
10	36C Wire Sys Inst/Op	499
10	63N M60A1/A3 Tank Sys Mech	286
10	68J Aircraft FC Repairer	148
10	91B Medical Specialist *	783
11	43E Parachute Rigger	100
12	57H Cargo Specialist	272
12	71N Traffic Mgmt Coordinator	163
13	62F Lifting/Loading Eq Op	129
13	71M Chapel Activities Sp	182
14	68G Aircraft Structural Rep	125
14	76C Eq Rec & Parts Sp	331
15	71L Administrative Sp *	2824
15	73C Finance Specialist	688
15	74D Computer/Tape Writer	132
15	75B Personnel Admin Sp	1061
15	76V Mat Stor & Hdlg Sp	216
15	93H Air Traffic Con Tower Op	114
15	96B Intelligence Analyst	218
16	74F Programmer/Analyst	95

* = MOS for Design A

(continued)

Table 13

Twenty-three Classification-Efficient Job Families for Design B

JOB FAMILY	MOS	n
1	05C Radio TT Operator *	2393
1	11B Infantryman *	6355
1	11C Indirect Fire Infmn	1494
1	13B Cannon Crmn *	6575
1	19D Cavalry Scout	1249
1	31V Tac Comm Sysop/Mech	515
1	63H Track Veh Repairer	335
1	64C Motor Transport Op *	3681
1	94B Food Service Sp *	3943
1	95B Military Police *	4516
2	05H Elec War/SIGINT INTER_IMC	171
2	98C Elec War/SIGINT Analyst	186
3	11H HV Anti-Armor Wpn Infn	979
3	13E Cannon Fire Direction Sp	627
3	55B Ammunition Sp *	288
3	76Y Unit Supply Sp *	1149
3	91E Dental Specialist	203
4	12B Combat Engineer *	3109
4	15D Lance Crmb/MLRS Sgt	281
4	63B Lt Wh Veh/Pwr Gen Mech *	1495
4	67N Utility Hel Repairer *	511
4	76W Petroleum Supply Sp *	664
5	12C Bridge Crewman	450
5	13F Fire Support Sp	693
5	19E M48-M60 Armor Crmn *	3297
5	62B Construction Equip Rep	233
5	62E HV Const Equip Rep	202
5	67V OBN/Scout Hel Rep	294
5	82C Field Artillery Surveyor	434
6	12F Engineer Tracked Crmn	151
7	16S MANPADS Crewmember *	596
7	31M Multichannel Comm Eq Op	2484
7	72E Combat Telecom Center Op	569
8	27E TOW/Dragon Rep *	363
9	27F Vulcan Repairer	130
9	52D Power Generation Equip Rep	178
10	31N Tactical Ckt Con	189
10	91P X-Ray Specialist	159
11	36C Wire Sys Inst/Op	499
11	68J Aircraft FC Repairer	148
11	91B Medical Specialist *	783
12	43E Parachute Rigger	100
13	54E NBC Specialist *	113
14	57H Cargo Specialist	272
14	71N Traffic Mgmt Coordinator	163
15	62F Lifting/Loading Eq Op	129
15	71M Chapel Activities Sp	182
16	63N M60A1/A3 Tank Sys Mech	286
17	63W Wheel Veh Mechanic	180
18	68G Aircraft Structural Rep	125
18	76C Eq Rec & Parts Sp	331
19	71L Administrative Sp *	2824
19	73C Finance Specialist	688
19	75B Personnel Admin Sp	1061
20	74D Computer/Tape Writer	132
20	96B Intelligence Analyst	218
21	74F Programmer/Analyst	95
22	76V Mat Stor & Hdlg Sp	216
22	93H Air Traffic Con Tower Op	114
23	92B Medical Lab Sp	310

(continued)

* = MOS for Design A

Table 14

Comparison of H_d/m[a] Indices Across Conditions

	DESIGN A		
	Project A Exp. Batt.	Project A ASVAB	McLaughlin ASVAB
Ceiling H_d/m[b]	3.340	1.377	0.759
12 CE Job Families	2.712	1.225	0.728
9 CE Job Families	2.264	1.074	0.683
6 CE Job Families	1.662	0.860	0.602
9 Operational Job Families	1.963	0.805	---

	DESIGN B	
	CE Method	Operational Method
Ceiling H_d/m[b]	4.490	4.490
23 Job Families	3.893	2.730
16 Job Families	3.545	2.350
9 Job Families	3.025	0.924

[a]The value m represents the number of assignment variables (i.e., job families).
[b]Ceiling values were calculated using all jobs individually before grouping into job families.

reduction in H_d expected when grouping jobs into job families. For example, for the Project A (Experimental Battery) condition in Design A, grouping 18 jobs into 9 job families using the CE method resulted in a one-third decrease in average H_d. For Design B, grouping 60 jobs into 23 job families using the CE method resulted in a one-sixth decrease in average H_d.

Table 14 also contains the average H_d indices (H_d/m) for the operational job families used in this research. For Design A, 18 jobs were grouped into the nine operational aptitude areas currently used by the Army and H_d values were calculated using both the Proj.A (Exp.Batt.) and Proj.A (ASVAB) data sources. Note that the average H_d values for the nine operational job families were substantially lower than the values for the nine CE job families for both data sources. For the Proj.A (ASVAB) data source, the average H_d value for the nine operational job families was even lower than for the six CE job family condition. For Design B, the average H_d values for the operational job families were also substantially lower than for the CE job families across all conditions.

Overall, comparisons of these average H_d results in Table 14 give preliminary but inconclusive evidence for many of the expected findings presented earlier. This evidence is inconclusive because, although it has been shown that H_d can be linked to MPP through its relationship to Brogden's measure of classification efficiency, this is a "back" sample relationship. Only by conducting simulations based upon the real data, generating MPP score, and statistically analyzing these scores can the evidence be conclusively presented in independent "cross" samples.

For Design A, examination of the jobs within each of the job families across all conditions shows that the CE clustering technique resulted in job families of varying sizes ranging anywhere from 1 job to 7 jobs. Across the sources of data, the Proj.A (Exp.Batt.) condition resulted in job families that shared some similiarities to the Proj.A (ASVAB) condition. For example, Infantryman and NBC Specialist clustered in the same family for both conditions and Combat Engineer and M48-M60 Armor Crewmember clustered together for both conditions. The "McLaughlin" data resulted in clusters that appeared to have little in common with either of the Project A concurrent validation data set clusters.

For Design B, the classification-efficient job families formed ranged in size from 1 job to 25 jobs. Comparison of these job families with the operational job families presented earlier

(see Tables 5, 6, and 7), revealed little similarity between in the two groupings. The operational job families contained generally logical groupings of similar types of jobs. The CE job families often grouped together more diverse types of jobs. The MOS in a priori job families are, of course, in a particular family because they appear to belong to that family. Thus, their higher face validity for membership in their family should not be surprising. Across all CE conditions, the first job family was always the largest, with the first job family gradually getting larger as the number of formed clusters decreased from 23 to 16 to 9. This first job family was generally composed of combat jobs, mechanic and repair jobs, and various other specialist jobs. The diversity of jobs in the CE job families indicates that it would not be easy to form classification-efficient clusters a priori.

There are two other indices that are important for evaluating the classification-efficient clusters and comparing them to the operational clusters. The first is the predictive validity or average weighted R^2 value across job family conditions, and the second is the average intercorrelation among the LSEs (r).

Table 15 provides a comparison of the average weighted R^2 values for all conditions. The average weighted R^2 value for each condition was calculated by weighting the R^2 values for each job family by the number of jobs in that job family, adding these values, and dividing by the total number of jobs. As with the H_d index, there was a maximum amount of R^2, calculated using each job individually, that acts as a ceiling for the highest average R^2 values possible for a given condition. From Table 15, note that even though the CE job families were formed based on H_d their average weighted R^2 values are fairly high in comparison to the ceiling values. Naturally, the 12 cluster and 23 cluster conditions were closest to the ceiling values calculated using all jobs (either 18 or 60 jobs). However, grouping the jobs into smaller sets of job families for Designs A and B also did not result in large decrements in R^2. This finding appears to be supportive of validity generalization (VG) theory and may be another excellent example of how DAT and VG are not necessarily inconsistent.

From Table 15, note also that the average weighted R^2 values for the operational job families are only slightly lower than the CE job families for both Designs A and B. Recall that there did appear to be fairly substantial differences between the operational job families and the CE job families in terms of the H_d index (see Table 14). Thus, it appears that the CE empirical

Table 15

Comparison of Average Weighted R^2 Indices Across Conditions

	DESIGN A		
	Project A Exp. Batt.	Project A ASVAB	McLaughlin ASVAB
Ceiling R^{2a}	.589	.437	.342
12 CE Job Families	.554	.428	.340
9 CE Job Families	.529	.419	.338
6 CE Job Families	.496	.407	.333
9 Operational Job Families	.508	.404	---

	DESIGN B	
	CE Method	Operational Method
Ceiling R^{2a}	.374	.374
23 Job Families	.364	.343
16 Job Families	.358	.336
9 Job Families	.349	.313

[a]Ceiling values were calculated as the average of the R^2 values computed separately for each job.

clustering method provided a meaningful improvement in H_d compared to the operational system with the predictive validity (R^2) of both methods remaining virtually identical.

The last important index that can be examined is the intercorrelations among the LSEs, r. Increasing the number of job families in a classification-efficient manner should decrease the intercorrelation among the LSEs. This effect occurs because each increase in the number of job families should provide greater uniqueness for the job families. Table 16 shows the average intercorrelations among the LSEs for the different job family conditions. As expected, for both of the Project A concurrent validation data sources in Design A, the average intercorrelation decreased steadily as the number of job families increased from 6 to 9 to 12. Unexpectedly, this relationship did not hold for the "McLaughlin" data source in Design A. In fact, the average intercorrelation for "McLaughlin" increased as the number of job families increased. However, with the number of jobs expanded to 60 in Design B for the "McLaughlin" data (see Table 16), the expected relationship of a decrease in the average intercorrelations when the number of job families increased was apparent. From Table 16, also note that the average intercorrelations among the LSEs for the nine operational job families in Design A fell just above the average for the nine CE job families for both data sources. Likewise, the average intercorrelations for the operational job families in Design B were greater than the average intercorrelations for the CE job families.

2. Selection-Efficient Job Families

The selection-efficient (SE) job clustering method developed for this research did not provide a solution that was at all credible in approximating the maximization of predictive validity (R^2). As discussed previously in the method section, the SE method developed for this research was a two-stage heuristic approach intended to provide a practical method of obtaining a close approximation to the highest possible predictive validity in a set of job clusters without having to evaluate every possible combination of jobs in terms of predictive validity.

The first stage of the algorithm was an initial combination of jobs into job clusters. For the six job family condition (Design A), this meant clustering the 18 jobs into six sets of families each containing three jobs. Sets of jobs were selected so that six non-overlapping families were chosen that had the highest R^2 values. The R^2 values for all possible sets of three jobs were computed and the triplet with no overlap with the first set that had the next highest R^2 was then

Table 16

Comparison of the Average Intercorrelations Among the LSEs for all Job Family Conditions

	DESIGN A		
	Project A Exp. Batt.	Project A ASVAB	McLaughlin ASVAB
12 CE Job Families	.699	.843	.876
9 CE Job Families	.720	.851	.862
6 CE Job Families	.763	.909	.833
9 Operational Job Families	.750	.873	---

	DESIGN B	
	CE Method	Operational Method
23 Job Families	.775	.906
16 Job Families	.805	.907
9 Job Families	.809	.973

selected. This process was continued until all jobs were placed in a selected triplet. For the 9 and 12 job family conditions, the 18 jobs were initially grouped into sets of two jobs (for the 12 job family condition most families had two jobs but a few had only one job).

The second stage of the algorithm involved shredding these initial clusters to determine if there were other combinations of jobs that had a higher predictive validity. This shredding process had a constraint that once jobs were added to an evolving cluster, that cluster was no longer eligible to be shredded. Without this constraint, the algorithm would have been infeasible because it would have been no different than evaluating all possible combinations of jobs.

Tables 17 and 18 give examples of six job families formed using the SE method for Proj.A (Exp.Batt) and Proj.A (ASVAB) data sources. The first column shows the initial set of clusters from the first stage and the second column shows the final set of clusters after the second stage shredding process. Although the initial set of clusters appeared perfectly reasonable, note that the overall average weighted R^2 value was not very high. In fact, examination of Table 15 presented earlier for the CE job families reveal that the CE job families had higher R^2 values than these SE job families. This was true for all conditions in this experiment.

It became apparent after examination of the data, that forcing the jobs into initial sets of clusters severely restricted the R^2 values. Some of the jobs individually had very high R^2 values, but they were forced together with one or two other jobs by the nature of the algorithm thereby lowering their potential contribution to R^2. The second stage shredding process was designed to eliminate these problems with the first stage. From examination of Tables 17 and 18, it can be seen that the second stage process provided only a slight increase in R^2. Once again it became apparent from examination of the data that the jobs which individually made the most contribution to R^2 were never isolated through this second stage of the algorithm. Instead, these jobs had other jobs combined with them, and due to the constraints of the algorithm this new job cluster was no longer eligible to be shredded.

Several attempts were made to develop reasonable alternative ways of forming selection-efficient clusters. A modification to the algorithm was attempted that shredded jobs beginning with the cluster that had the highest R^2 value instead of the lowest R^2 value. This was an attempt to provide an opportunity for the jobs that contributed the most to overall R^2 to be

Table 17

Six Job Families for Project A (Experimental Battery) Using Selection-Efficient Clustering Method

Initial Clusters	R^2	After Shredding	R^2
Job Family 1	0.711	Job Family 1	0.651
TOW/DRAGON Repairer Petroleum Supply Specialist Food Service Specialist		TOW/DRAGON Repairer Petroleum Supply Specialist Food Service Specialist Infantryman	
Job Family 2	0.571	Job Family 2	0.625
Infantryman Combat Engineer M48-M60 Armor Crewmember		Combat Engineer M48-M60 Armor Crewmember	
Job Family 3	0.515	Job Family 3	0.515
MANPADS Crewmember Single Channel Radio Operator NBC Specialist		MANPADS Crewmember Single Channel Radio Operator NBC Specialist	
Job Family 4	0.443	Job Family 4	0.443
Ammunition Specialist Administrative Specialist Unit Supply Specialist		Ammunition Specialist Administrative Specialist Unit Supply Specialist	
Job Family 5	0.381	Job Family 5	0.381
Light Wheel Vehicle Mechanic Utility Helicopter Repairer Medical Specialist		Light Wheel Vehicle Mechanic Utility Helicopter Repairer Medical Specialist	
Job Family 6	0.246	Job Family 6	0.246
Cannon Crewmember Motor Transport Operator Military Police		Cannon Crewmember Motor Transport Operator Military Police	
Average Weighted R^2 = 0.477893		Average Weighted R^2 = 0.478225	

Table 18

Six Job Families for Project A (ASVAB) Data Using Selection-Efficient Clustering Method

Initial Clusters	R^2	After Shredding	R^2
Job Family 1	0.629	Job Family 1	0.536
Combat Engineer TOW/DRAGON Repairer Petroleum Supply Specialist		Combat Engineer TOW/DRAGON Repairer Petroleum Supply Specialist Infantryman M48-M60 Armor Crewmember NBC Specialist	
Job Family 2	0.493	Job Family 2	0.620
M48-M60 Armor Crewmember NBC Specialist Food Service Specialist		Food Service Specialist	
Job Family 3	0.416	Job Family 3	0.418
Infantryman Single Channel Radio Operator Unit Supply Specialist		Single Channel Radio Operator Unit Supply Specialist	
Job Family 4	0.361	Job Family 4	0.361
MANPADS Crewmember Administrative Specialist Medical Specialist		MANPADS Crewmember Administrative Specialist Medical Specialist	
Job Family 5	0.296	Job Family 5	0.296
Ammunition Specialist Light Wheel Vehicle Mechanic Utility Helicopter Repairer		Ammunition Specialist Light Wheel Vehicle Mechanic Utility Helicopter Repairer	
Job Family 6	0.182	Job Family 6	0.182
Cannon Crewmember Motor Transport Operator Military Police		Cannon Crewmember Motor Transport Operator Military Police	
Average Weighted R^2 = 0.396380		Average Weighted R^2 = 0.399455	

isolated. Although some different rearrangements of the jobs resulted from this procedure, average weighted R^2 values were not increased. Another attempt was made to apply the second stage shredding process to the classification-efficient clusters. The idea was to try to substantially increase the R^2 values of the CE clusters by rearranging the jobs and designate this new set of families as the SE job families. Not surprisingly, given the already high R^2 values for the CE clusters, this procedure resulted in little or no improvement in average weighted R^2 values.

Given these disappointing results for the SE clustering method, it became obvious that there was nothing to gain in retaining this condition in the basic research design (Design A-1). Without any viable SE job families, it was not desirable to include this condition as part of the model sampling experiment. This change meant that Design A-1 was modified to contain only two independent variables forming a 3 x 3 design. Designs A-2 and A-3 were not affected by these changes. For Design A-2, the CE job clusters represented the "empirical" method of clustering to be compared with the Army's operational clusters (see Table 2). Additionally, there would have been no point in using this SE algorithm with the 60 jobs in Design B, so that the CE job clustering method also represented the "empirical" method of clustering for Design B.

B. Model Sampling Experiment Results

The model sampling experiment involved the simulated assignment of 20 cross-samples of entities to job families under 12 different experimental assignment conditions for Design A and 6 different experimental assignment conditions for Design B. Table 19 shows the MPP standard scores averaged across the 20 replications for each assignment condition for Designs A-1, A-2, and A-3. Table 20 shows the MPP standard scores averaged across the 20 replications for each assignment condition for Design B.

Before performing any statistical tests on these results, it was first necessary to separate out the effects due to classification from the effects due to selection. This research is concerned with demonstrating the benefits in terms of increased classification effects under differing experimental conditions. For this reason, it was desirable to subtract out of the MPP values the

Table 19

Means and Standard Deviations of MPP Standard Scores for all Conditions in Design A

DESIGN A-1: Classification-Efficient Job Clustering Method/Assignment with FLS Composites

	Project A Exp. Batt. D1	Project A ASVAB D2	McLaughlin ASVAB D3
J1: 6 Job Families	.464 (.037)	.416 (.045)	.278 (.036)
J2: 9 Job Families	.539 (.039)	.470 (.046)	.261 (.039)
J3: 12 Job Families	.592 (.049)	.502 (.052)	.286 (.040)

DESIGN A-2: Empirical (CE Clustering) versus Army Operational Job Families/ Assignment with FLS Composites

	Project A Exp. Batt. D1	Project A ASVAB D2
M1: Empirical[a] 9 Job Families	.539 (.039)	.470 (.046)
M2: Operational 9 Job Families	.505 (.048)	.439 (.041)

DESIGN A-3: Army Operational Job Families/Assignment with Aptitude Areas

	Project A Aptitude Areas D1
M2: Operational 9 Job Families	.317 (.050)

Note. Standard deviations appear in parentheses below means.
[a]Values for Empirical conditions come directly from Design A-1.

Table 20

Means and Standard Deviations of MPP Standard Scores for all Conditions in Design B

DESIGN B: McLaughlin Data with 60 Jobs/Assignment with FLS Composites

	Clustering Method	
	Empirical[a] M1	Operational M2
J1: 9 Job Families	.480 (.033)	.349 (.032)
J2: 16 Job Families	.545 (.036)	.472 (.037)
J3: 23 Job Families	.588 (.034)	.511 (.034)

Note. Standard deviations appear in parentheses below means.
[a]Classification-efficient clustering method.

contribution due to selection effects leaving only the contribution due to classification. This process can be accomplished by using the Naylor-Shine equation and table for determining the increase in mean criterion score obtained by using a selection device (Naylor & Shine, 1965). The basic equation underlying the Naylor-Shine approach is:

$$Z_{yi} = r_{xy} \frac{d_i}{s_i}$$

where,

Z_{yi} = the mean criterion score (in standard score units) of all cases above predictor cutoff

r_{xy} = the validity coefficient

d_i = the ordinate of the normal distribution at the predictor cutoff

s_i = the selection ratio.

A selection ratio of .75 was used in all of the simulations conducted for this research. In addition, the AFQT was used as the selection device so it is the validity of the AFQT that is used in this equation. The average AFQT validity for the Project A concurrent validation data sources was calculated as 0.531. The average AFQT validity for the "McLaughlin" data with 18 jobs was 0.4905. These validities are different because the Project A concurrent validation data utilizes the CTP criterion and the "McLaughlin" data set utilizes the SQT criterion. The average AFQT for the "McLaughlin" data with 60 jobs was 0.504. Calculation of Z_{yi} yields an expected MPP due to selection alone of 0.225 for the Project A data sources, 0.2078 for the "McLaughlin" data set with 18 jobs, and 0.214 for the "McLaughlin" data set with 60 jobs. These constant values were subtracted from the MPP standard score values for the appropriate conditions shown in Tables 19 and 20. The revised set of means representing only the effects due to classification are shown in Tables 21 and 22.

In the next sections, the results shown in Tables 21 and 22 are discussed in terms of the expected findings stated earlier. The discussion of the statistical analyses will be presented first for Design A and then for Design B.

1. <u>Design A: Number of Job Families</u>

One of the primary expected findings of this research states that the magnitude of the MPP scores will increase significantly as the number of job families increases from 6 to 9 and

Table 21

Means of MPP Standard Scores for all Conditions in Design A for Effects Due Only to Classification

DESIGN A-1: Classification-Efficient Job Clustering Method/Assignment with FLS Composites

	Project A Exp. Batt. D1	Project A ASVAB D2	McLaughlin ASVAB D3
J1: 6 Job Families	.239	.191	.070
J2: 9 Job Families	.314	.245	.054
J3: 12 Job Families	.367	.277	.078

DESIGN A-2: Empirical (CE Clustering) versus Army Operational Job Families/ Assignment with FLS Composites

	Project A Exp. Batt. D1	Project A ASVAB D2
M1: Empirical[a] 9 Job Families	.314	.245
M2: Operational 9 Job Families	.280	.214

DESIGN A-3: Army Operational Job Families/Assignment with Aptitude Areas

	Project A Aptitude Areas D1
M2: Operational 9 Job Families	.092

[a]Values for Empirical conditions come directly from Design A-1.

Table 22

Means of MPP Standard Scores for all Conditions in Design B for Effects Due Only to Classification

DESIGN B: McLaughlin Data with 60 Jobs/Assignment with FLS Composites

	Clustering Method	
	Empirical[a] M1	Operational M2
J1: 9 Job Families	.266	.135
J2: 16 Job Families	.331	.258
J3: 23 Job Families	.374	.297

[a]Classification-efficient clustering method.

then to 12 job families. On simple inspection of Table 21, it can be seen that the rank order of magnitude of MPP scores fell in the hypothesized direction for two of the three data sources.

The statistical significance of these differences was addressed by performing a 3 x 3 repeated measures analysis of variance. The results from this analysis are presented in Table 23. Both main effects and the interaction between the data source factor and the job family factor were significant ($p < .0001$). Because it was apparent that the "McLaughlin" data source did not support the number of job families hypothesis, a separate 2 x 3 repeated measures ANOVA was subsequently performed for only the Project A concurrent validation data sources. Discussion of the results for the "McLaughlin" data will be presented in a later section on types of criteria.

The results from the subsequent analysis on only the Project A concurrent validation data sources are presented in Table 24. Once again, both main effects and the interaction between the data source factor and the job family factor were significant. Thus, for the two Project A data sources, the significant main effect of J allowed the null hypothesis of no difference between the means for 6, 9, and 12 job families to be rejected with a high level of confidence ($p < .0001$). The significant interaction term indicates that the two Project A data sources were affected differently by the increase from 6 to 9 to 12 job families. Examination of the data revealed that the Proj.A (Exp.Batt) data source resulted in slightly greater increases in MPP from 6 to 9 to 12 job families than did the Proj. A (ASVAB) data source.

A second expected finding investigated in the research involving the number of job family conditions predicts that the efficiency of classification will vary according to a negatively accelerated function such that the increase in MPP from 6 to 9 job families will be greater than the increase in MPP from 9 to 12 job families. From examination of the means in Table 21, this hypothesis appears to hold for the Project A data sources. This hypothesis was statistically tested with the use of paired-comparison t-tests for each of the Project A data sources. The difference between each MPP value from 6 to 9 job families was compared to the difference between each MPP value from 9 to 12 job families. The null hypothesis states that the difference between these two comparisons is zero. Confirmation of the hypothesis occurs if the difference from 6 to 9 job families is greater than difference from 9 to 12. Thus, a one-tailed t-test is appropriate for this situation.

Table 23

Repeated Measures ANOVA of MPP Standard Scores for Design A

Sources of Variation	SS	df	MS	F	p
$D_{(data\ source)}$	1.823	2	0.9114	1381.85	<.0001
Error (d)	0.0250627	38	0.0006595		
$J_{(\#\ of\ job\ families)}$	0.1650	2	0.0825	229.12	<.0001
Error (j)	0.013684	38	0.00036011		
D x J	0.0831	4	0.0208	102.28	<.0001
Error (dj)	0.0154	76	0.00020309		

Note. A two factor repeated measure design is described by Winer, Brown and Michels (1991) p. 561. Error (d) equals Dx subj. w. groups.

Table 24

Repeated Measures ANOVA of MPP Standard Scores: Comparison of Proj.A (Exp. Batt) and Proj.A (ASVAB) Data Sources for all Job Family Levels

Sources of Variation	SS	df	MS	F	p
$D_{(data\ source)}$	0.1438	1	0.1438	297.24	<.0001
Error (d)	0.0091942	19	0.0004839		
$J_{(\#\ of\ job\ families)}$	0.2331	2	0.1165	489.16	<.0001
Error (j)	0.0090529	38	0.0002382		
D x J	0.0087	2	0.0044	20.28	<.0001
Error (dj)	0.00818	38	0.0002153		

Note. A two factor repeated measure design is described by Winer, Brown and Michels (1991) p. 561. Error (d) equals Dx subj. w. groups.

As predicted, for the Proj.A (Exp.Batt), the difference from 6 to 9 job families was significantly greater than the difference from 9 to 12 job families, $t(19) = 3.29$, $p < .003$. For the Proj.A (ASVAB) data source, the difference from 6 to 9 job families was also significantly greater than the difference from 9 to 12 job families, $t(19) = 3.12$, $p < .005$. Thus, there does appear to be evidence from these results to support the proposition that the efficiency of classification varies with the number of job families according to a negatively accelerated function.

2. Design A: Job Clustering Methods

Initially, one of the major expected findings of this research was that the CE method of job clustering would result in significantly greater MPP scores than the SE method. Because the SE job clustering method was not successful in producing job clusters that maximized selection-efficiency, the SE algorithm was no longer a credible alternative and this hypothesis was no longer worth testing. However, another major expected finding of this research stated that an empirical method of clustering (i.e., the CE method) would result in significantly greater MPP scores than the current U.S. Army operational job families. This hypothesis is testable and is represented in Table 21 as Design A-2.

On simple inspection of Table 21, one can see that the operational MPP standard scores (i.e., the results obtained on the 9 operational families) for Design A-2 are lower than the empirical MPP standard scores (i.e., the results obtained for the CE families) for both data source conditions. Table 25 provides the results for the repeated measures ANOVA of Design A-2. Note that the main effects for the clustering methods factor and the data source factor are both significant. Thus, there is support for the hypothesis that the empirical CE method of clustering resulted in significantly greater MPP scores than the operational job family method. Note that the interaction between data source and clustering method is not significant. From the means in Table 21 for Design A-2, it is apparent that the differences between the empirical and operational methods were virtually identical for both data sources eliminating any interaction effect.

3. Design A: Type of Predictor Measure

The availability of the Project A concurrent validation experimental battery (20 experimental predictors added to the 9 ASVAB tests) allowed a determination of the effects on

Table 25

Repeated Measures ANOVA of MPP Standard Scores for Design A-2

Sources of Variation	SS	df	MS	F	p
$D_{(data\ source)}$	0.0907	1	0.0907	252.23	<.0001
Error (d)	0.0068320	19	0.0003596		
$M_{(clustering\ method)}$	0.0209	1	0.0209	85.87	<.0001
Error (m)	0.0046182	19	0.0002431		
D x M	0.00004	1	0.00004	0.11	<.7394
Error (dm)	0.0071946	19	0.0003787		

Note. A two factor repeated measure design is described by Winer, Brown and Michels (1991) p. 561. Error (d) equals D x subj. w. groups.

MPP of expanding the predictor space to include spatial, psychomotor, biodata, and interest predictors. The use of the full set of experimental plus ASVAB predictors (29 tests) for job clustering and assignment was compared to the use of only the 9 ASVAB tests. As discussed earlier, the composition of the job families formed using the Proj.A (Exp.Batt) predictors shared some similiarities to the job families formed using the Proj.A (ASVAB) predictors. In terms of the resulting MPP scores after assignment, however, note from Table 21 that in all cases the Proj.A (ASVAB) means are lower than the Proj.A (Exp.Batt) means. In addition, from the repeated measures ANOVAs presented in Tables 24 and 25, it is apparent that this data source factor is significant for all conditions in both Designs A-1 and A-2. Thus, there is evidence to support the hypothesis that when assignment variables are based on all 29 Project A tests, MPP will be significantly greater than when the assignment variables are based on the standard 9 ASVAB tests.

4. Design A: Type of Criterion Measure

The purpose of matching the same 18 jobs in the Project A data and the "McLaughlin" data for Design A was to directly compare the effects on classification efficiency of using more routinely and inexpensively collected criterion (i.e., SQTs and training grades) with the specially designed Project A criteria (i.e., CTP). It was hypothesized that there would be no significant difference in MPP scores due to the use of assignment variables based on the Project A criterion and the "McLaughlin" criterion.

As Table 21 shows, the mean MPP scores after removal of selection effects are much lower for the "McLaughlin" data condition than for the Project A (ASVAB) condition. Table 26 shows a 2 x 3 repeated measures ANOVA of the MPP standard scores comparing the Proj.A (ASVAB) and "McLaughlin" data sources. These two data sources were isolated for comparison across the job family conditions because they both share the same predictors (i.e., the ASVAB) but differ in terms of criterion measures. Table 26 shows that contrary to the stated hypothesis of no difference, there was a significant difference between the data sources.

An additional prediction was also stated to allow for statistically significant differences between the two data sources (Project A concurrent and "McLaughlin"), if the conclusions reached about the other expected findings in this research were the same with both data sources. In other words, if the conclusions about the effect on classification efficiency of increasing the

Table 26

Repeated Measures ANOVA of MPP Standard Scores: Comparison of Proj.A (ASVAB) and "McLaughlin" Data Source for all Job Family Levels

Sources of Variation	SS	df	MS	F	p
$D_{(data\ source)}$	0.8696	1	0.8696	955.87	<.0001
Error (d)	0.0172847	19	0.0009097		
$J_{(\#\ of\ job\ families)}$	0.0451	2	0.0226	65.06	<.0001
Error (j)	0.0131771	38	0.0003468		
D x J	0.0374	2	0.0187	91.70	<.0001
Error (dj)	0.0077492	38	0.0002039		

Note. A two factor repeated measure design is described by Winer, Brown and Michels (1991) p. 561. Error (d) equals Dx subj. w. groups.

number of job families were the same for both "McLaughlin" and Project A concurrent data, but the "McLaughlin" MPP values were somewhat lower overall, this prediction could still be supported.

Unfortunately, even this second hypothesis did not hold. From Table 21, one can see that the "McLaughlin" data source resulted in a reversal of MPP values from 6 to 9 job families. Table 27 presents a repeated measures ANOVA for just the "McLaughlin" data source across all three job family levels. Note from Table 27 that although the mean differences across the job family conditions (see Table 21) appear very slight, they were statistically significant.

Additional statistical comparisons of the job family levels for the "McLaughlin" data revealed that the 6 job family condition (J1) was not significantly different from the 12 job family condition (J3), $F(1,19) = 1.43$, $p < .2468$. However, the 9 job family condition (J2) was significantly different from both the 6 job family condition, $F(1,19) = 9.28$, $p < .0066$, and the 12 job family condition, $F(1,19) = 33.66$, $p < .0001$.

These Design A results are unfortunate in that they do not provide preliminary evidence of the usefulness of the "McLaughlin" validity data with the SQT criterion for the structuring of jobs into families. However, the usefulness of Design B with its 60 job permits the examination of important methodological issues, even if we cannot argue for the immediate usefulness of SQT validity data as the primary basis of a restructuring of Army job families. The results found for Design A with only 18 jobs for the "McLaughlin" data could be caused by the interaction of a variety of factors. First, with only 18 jobs the somewhat poorer psychometric properties of the SQT criterion (e.g., criterion-referenced, lack of discriminability) compared to the CTP criterion could have contributed to the inconsistent findings. Recall that there was an unexpected reversal of the results for the intercorrelations among the LSEs, r, for the "McLaughlin" data with 18 jobs. These reversals in the intercorrelation magnitudes due to the psychometric properties of the data could be an explanation for these inconsistent findings. From Brogden's (1959) formulation it is known that r is an important component in the estimation of MPP. Thus, although Horst's differential index, H_d, and the predictive validity, R^2, indicated that MPP should increase as the number of job families increased, the average intercorrelations among the LSEs across the conditions indicated otherwise.

Table 27

Repeated Measures ANOVA of MPP Standard Scores for the "McLaughlin" Data Source Across Job Family Levels

Sources of Variation	SS	df	MS	F	p
$J_{(\# \text{ of job families})}$	0.0063	2	0.0032	10.08	<.0003
Error (j)	0.01188474	38	0.00031276		

Note. Error (j) equals Jx subj. w. groups.

Second, it is important to recall that in Design A, although the "McLaughlin" data with the SQT/training criterion was used for job clustering and calculation of assignment weights, evaluation of assignment and calculation of the MPP results was based on the designated population values. This design was used to carefully control the error that results from the use of the same sample for computing weights for assignment and evaluation. The designated population for Design A was the Project A concurrent validation data with the full set of 29 predictors and the CTP criterion. Thus, Design A was based on the assumption that the Project A population parameters for both predictors and criterion represented "truth" in the population. Using different content (e.g., CTP criterion) to evaluate the effect of assignment variables obtained using the "McLaughlin" data (with the SQT/training criteria) is the major factor contributing to the overall low MPP values obtained using the "McLaughlin" data as the source of assignment variables in Design A.

Finally, because of the desire to have the same 18 jobs included for "McLaughlin" data source condition as were contained in the Project A data for Design A, some compromises were made that may have influenced the results. Three out of the 18 jobs were included that had end-of-course training scores as criterion instead of SQT scores. Even though every attempt was made to equalize these two criterion sources, the training scores are known to have even poorer psychometric properties than the SQT criterion. In Design B, these same three jobs with the training criterion were also included, but there were an additional 57 jobs instead of 15 jobs so that the influence of these three jobs should not be as great.

The conclusions from Design A regarding SQT apply to a methodological study that assumes that the concurrent validation Project A CTP criterion represents "truth" in the population. In Design B, we use the SQT to investigate methodological hypotheses because it was the best sample of validities available over a large number of jobs. Alternatively, we could have constructed values for a validity matrix by judgment and by aggregating data from several other studies. Such an approach could have been defended for this methodological study. However, we wanted a matrix of validities which would behave as much as possible like real validity coefficients. In addition, in Design B, remember that the SQT criterion was used for computing both assignment weights and evaluation weights. Under these circumstances, we believe that the validity matrices based on the SQT criterion have the same statistical

characteristics (although on the average somewhat lower) as would similar validities, if available based on the CTP criterion. Therefore, the findings from Design A did not deter us from proceeding with a similar methodological study for Design B using the SQT criterion.

5. Design A: FLS Assignment versus Aptitude Area Assignment

The present research presented an opportunity to compare the use of FLS composites for assignment directly to the use of the aptitude area composites. Table 21 (Design A-3) gives that part of the MPP score remaining after that part of the total MPP due to selection has been subtracted for the condition in which entities were assigned to the 9 operational job families with the use of the Army aptitude area composites. Note that this value was very low indicating very little classification potential when the current aptitude area composites are used for assignment.

The expected finding stated that any condition involving FLS assignment would result in significantly greater MPP scores than assignment based upon the Army operational aptitude area composite. By comparing the single cell result in Design A-3 with the lowest MPP using Project A data from either of the other two designs (A-1 or A-2), it is possible to conclude that any condition involving FLS assignment is better than aptitude area assignment. The lowest MPP score for either Design A-1 or A-2 using Project A data resulted when the Proj.A (ASVAB) data was used for FLS assignment to the 6 CE job families. As expected, assignment with FLS for this lowest condition (M = .191) was significantly better than assignment with aptitude area composites (M = .092), $F(1,19) = 680.18$, $p < .0001$. Thus, there was substantial support from these results for the hypothesis that FLS assignment resulted in significantly greater MPP scores than aptitude area assignment.

6. Design B: Number of Job Families

From Table 22, it is apparent that the magnitude of the MPP scores increased as the number of job families increased from 9 to 16 and then to 23 job families. The statistical significance of these differences was addressed by performing a 2 x 3 repeated measures analysis of variance. The results from this analysis are presented in Table 28. Both main effects and the interaction between the clustering method factor and the job family factor were significant ($p < .0001$). The significant interaction term indicates that the two clustering methods were affected differently by the increase from 9 to 16 to 23 job families. Examination of the data

Table 28

Repeated Measures ANOVA of MPP Standard Scores for Desgin B

Sources of Variation	SS	df	MS	F	p
$D_{(clustering\ methods)}$	0.2633	1	0.2633	6297.30	<.0001
Error (d)	0.0007945	19	0.0000418		
$J_{(\#\ of\ job\ families)}$	0.3814	2	0.1907	3289.39	<.0001
Error (j)	0.0022031	38	0.00005798		
D x J	0.0211	2	0.0105	330.65	<.0001
Error (dj)	0.00121233	38	0.0000319		

Note. A two factor repeated measure design is described by Winer, Brown and Michels (1991) p. 561. Error (d) equals Dx subj. w. groups.

revealed that the use of the operational clusters resulted in greater increases in MPP from 9 to 16 job families than did the empirical clusters.

Similar to Design A, it was expected that the efficiency of classification would vary with the number of job families according to a negatively accelerated function such that the increase in MPP from 9 to 16 job families would be greater than the increase in MPP from 16 to 23 job families. From examination of the means in Table 22, it appears that there is support for this hypothesis. A paired comparison t-test was performed for each of the clustering methods (empirical vs. operational). The difference between each MPP value from 9 to 16 job families was compared to the difference between each MPP value from 16 to 23 job families. Once again, a one-tailed t-test was used for this statistical test.

As predicted, for the empirical CE clustering condition, the difference from 9 to 16 job families was significantly greater than the difference from 16 to 23 job families, $t(19) = 6.87$, $p < .0001$. For the operational clustering condition, the difference from 9 to 16 job families was also significantly greater than the difference from 16 to 23 job families, $t(19) = 18.97$, $p < .0001$. Thus, once again, there does appear to be evidence from these results to support the proposition that the efficiency of classification varies with the number of job families according to a negatively accelerated function.

7. Design B: Job Clustering Methods

It was expected that the empirical, classification-efficient method of clustering would result in significantly greater MPP scores than the operational methods of clustering (aptitude areas, CMF categories, and a combination of these two groupings). Upon simple inspection of Table 22, it is apparent that for all job family conditions the empirical MPP scores were greater than the operational MPP scores. The repeated measures analysis of variance presented earlier in Table 28 also provides the statistical test for this set of conditions. Note from Table 28 that the main effect for the clustering methods factor was significant ($p < .0001$). The interaction between the clustering methods factor and the job family factor noted earlier can be explained further by noting that the differences in mean MPP between the empirical and operational methods were fairly consistent for the 16 and 23 job family conditions (i.e., .073 and .077, respectively). However, the differences in mean MPP between the empirical and operational methods for the 9 job family condition were almost double at .131. This indicates

that the operational 9 job families based upon the aptitude areas performed even more poorly than expected resulting in an interaction effect.

8. Effect of Sample Size

This study also contributes to our knowledge of the effect that analysis sample size has on MPP computed in independent samples. This effect is true for research designs in which the regression weights for FLS composites are computed in the analysis sample and MPP computed in one or more cross-samples. This knowledge is based on inclusive information that relates to only one condition of Design A -- the condition in which FLS experimental composites are the AVs to optimally assign entities to 12 CE empirically formed families.

Design A used analysis samples to form AVs which could be characterized as moderate in size. A companion study by Whetzel (1991) exists in which the analysis sample used to compute the AVs for use in a comparable condition is infinitely large. The use of the designated population as the analysis sample implies that the analysis sample is infinitely large. We wish to estimate the correction factor which should be applied to values of MPP computed using analysis samples of infinite size in order to estimate what the value of MPP would have been if the analysis samples had been of the size used in Design A.

Whetzel (1991) provided an MPP value for the results of a simulation in which the close equivalent of FLS-experimental composites serve as AVs for assignment to 11 out of the 18 jobs. These 11 were selected because they most completely spanned the joint predictor-criterion space defined by 11 of the 18 jobs. Therefore these 11 jobs would be expected to provide a higher potential classification efficiency than obtained in the 12 job family condition of Design A. The MPP provided from classification effects, that is, after the component of MPP due to selection is removed, should also be larger since the Whetzel (1991) study used a more efficient selection variable ("g" instead of AFQT).

The MPP standard score obtained in Whetzel (1991) for a somewhat comparable condition to the Design A condition described above is .722. This contrasts with the MPP standard score for the Design A condition of .592 yielding a difference of .130 and a correction factor of .180. As noted above, this correction factor is an overestimate for the Design A data on two counts. Thus, we estimate that the proper value of this correction factor lies between .10 and .15. Since the empirical samples of Design B have an average size of over twice those

of Design A and the AVs corresponding to the families are based on a division of 60 jobs among the 11 or 12 families, instead of the division of 18 jobs, this estimate obtained from Design A must be an over estimate of the correction factor for Design B. Considering all of the above, we estimate that the correction factor for Design B (i.e., the multiplier to be applied to the obtained MPPs to provide unbiased estimates of MPP), could conservatively be estimated to fall between .05 and .10. This correction factor could be applied to the MPP values of Table 22 to adjust for the possible effects of correlated error between assignment and evaluation variable (even though these values are cross-sample results).

C. Estimating the Practical Significance of Gains in MPP

Finding statistical significance permits consideration of the practical significance of the MPP values across the various experimental conditions. It is possible to calculate percentage gains in MPP for various conditions of interest from the mean MPP values presented in Tables 21 and 22. Actual gains in MPP standard scores also can be translated directly into dollar estimates of the value of increased productivity using the cost and benefits analyses of Nord and Schmitz (1989, 1991).

Nord and Schmitz (1989, 1991) conducted a utility analysis of the merits of alternative manpower policies for the U.S. Army. Their goal was to obtain realistic estimates of the costs and benefits of changing job entry standards and allocation procedures. To determine dollar estimates, Nord and Schmitz (1989, 1991) used a net present value (NPV) model for performance valuation which is a refinement of the approach developed by Brogden (1951) and developed further by many other personnel testing researchers (Boudreau, 1983; Cascio, 1987; Hunter & Schmidt, 1982).

Nord and Schmitz (1989, 1991) found that optimal assignment using FLS prediction (based on aptitude areas rather than ASVAB test scores) resulted in a .143 increase in mean predicted performance over assignment using the current Army selection and classification system. The net economic value of this gain was estimated to be $262 million for one year. This estimate will be used to provide a basis for extrapolating utility estimates from the results of the present study.

In using this estimate for the present study, it is assumed that the dollar values are linear throughout the range of performance values. It is also important to point out that Nord and Schmitz's costing estimates were based on 1988 costs. Thus, the $262 million would be a slight underestimate of today's value. However, Nord and Schmitz based their estimates on 1984 entry-level accessions of 120,000 per year. This rate of accession has actually declined over the past several years. This would suggest that the $262 million is a slight overestimate of today's values. For the purposes of approximating economic values for the present research, it will be assumed that these two factors tend to balance one another and that the $262 million is a good estimate for extrapolation purposes.

Interpreting gains in MPP with dollar value estimates is important because it gives some concrete meaning to the increases observed in MPP values. Dollar value estimates provide a scale for comparison of alternative policies and comparison to other research in this same area. The dollar values that are given, however, should not be considered absolute expected increases since each organization needs to determine its own dollar values. Although these dollar value estimates were extrapolated directly from the comprehensive utility analysis completed by Nord and Schmitz (1989, 1991), it is important to point out that there were certain operational constraints that were not taken into account in this simulation that could affect the utility benefits to the Army. For example, in this simulation, equal quotas per job were used instead of operational quotas needed by the Army, and each job was considered to have equal value to the organization. In addition, it was not possible to take into account operational constraints such as sex (certain Army jobs are not open to women and both combat support and combat service support units have quotas for women soldiers) and availability of training slots. Also, this simulation assumed that individuals would accept the job to which they have been optimally assigned. Since the Army is a volunteer system, this is an operational problem that must be confronted in setting up an efficient selection/classification system. This last problem is mitigated somewhat with the use of job families. Assignment to job families and then consideration of preferences in the further assignment to the jobs within these families could allow for enough freedom of choice to satisfy many potential recruits.

Table 29 gives the differences and percentage gains between the average MPP scores from Tables 21 and 22 for all of the major comparisons for the hypotheses stated earlier. It is

Table 29

Differences and Percentage Gains in MPP scores for all Major Comparisons

DESIGN A

Number of Job Families	Project A Experimental Battery Difference	Project A Experimental Battery % Gain	Project A ASVAB Difference	Project A ASVAB % Gain
Increase from:				
6 to 9	.075	31.3	.055	28.7
9 to 12	.053	16.9	.032	12.9
6 to 12	.128	53.5	.086	45.3

Clustering Method	Project A Experimental Battery Difference	Project A Experimental Battery % Gain	Project A ASVAB Difference	Project A ASVAB % Gain
Empirical over Operational	.034	12.0	.031	14.4

Type of Predictor	Average Across Job Families Difference	Average Across Job Families % Gain
Project A (Exp.Batt) over Project A (ASVAB)	.069	29.1

FLS versus Aptitude Area Assignment	Project A ASVAB Difference	Project A ASVAB % Gain
Empirical w/FLS over Operational w/AA	.153	166.3
Operational w/FLS over Operational w/AA	.122	132.6

(continued)

Table 29 (continued)

DESIGN B

Number of Job Families	Empirical Difference	Empirical % Gain	Operational Difference	Operational % Gain
Increase from:				
9 to 16	.065	24.4	.123	91.1
16 to 23	.043	13.0	.039	15.1
9 to 23	.108	40.6	.162	120.0

Clustering Method	Average Across Job Families Difference	Average Across Job Families % Gain
Empirical over Operational	.094	40.9

apparent that increasing the number of job families has a significant effect on MPP scores. For Design A, the percentage gains from increasing the number of job families from 6 to 9 ranged from 28% to 31%. The percentage gains from increasing the number of job families from 9 to 12 ranged from 12% to 17%. For Design B, increasing the number of job families from 9 to 16 resulted in gains of 24.4% in MPP when CE clustering was used, and gains of 91.1% when the operational clusters were used. Increasing the number of job families from 16 to 23 resulted in gains of 13% in MPP when CE clustering was used, and gains of 15.1% when the operational clusters were used.

From Design A, it is possible to address the operational question of the dollar value that would be "lost" to the Army if the number of job families was decreased from 9 to 6. Decreasing the number of job families has been the recommendation of recent research in the Army (McLaughlin et. al, 1984). The results from the present research show that, for the Proj.A (Exp.Batt) condition, the difference of .075 between 9 and 6 job families represents approximately $137 million dollars per year that could be lost by decreasing the number of job families. For the Proj.A (ASVAB) condition, the difference of .055 between 9 and 6 families represents approximately $100 million dollars per year lost.

It is also possible to address the question of how much improvement the Army could expect by increasing the number of job families. The results from Design B provide the most dramatic illustration of the dollar value improvements possible for the Army. For example, note that if the current nine operational job families (aptitude areas) were abandoned in favor of 16 operational job families (combination of aptitude area and CMF) a percentage gain of 91.1% could be expected which translates into a $225 million dollar per year improvement. Alternatively, if the current nine operational job families (aptitude areas) were abandoned in favor of 23 operational job families (CMF categories) a gain of 120% could be expected which translates into a $297 million dollar per year improvement. Furthermore, if the Army utilized the CE method of clustering developed in this research to cluster jobs into 23 job families, the expected dollar value improvement would be approximately $438 millon dollars per year over the current 9 operational job families.

Another comparison of interest is the gain in MPP that can be attributed to using the empirical CE method of clustering instead of the operational methods currently used by the

Army. From Design A, the results showed gains of only 12% to 14% for the empirical nine job families over the operational nine job families. From Design B, with the much more realistic and broader range of job families, the results showed gains of 40% when averaged across job families. This 40% gain translates into a $172 million dollar per year improvement to the Army that could accrue from using a CE method of clustering for forming job families.

Table 29 also shows the difference between the two types of predictors that were part of Design A. The difference among the types of predictors suggest that if the Army were to adopt an expanded set of experimental predictors added to the ASVAB instead of the ASVAB alone, they could expect MPP improvements of .069 representing a 29.1% gain in MPP. This gain translates into an improvement worth $126 million per year.

Finally, from the section comparing FLS assignment to aptitude area assignment in Table 29 (only Design A), it is apparent that FLS assignment is substantially better than aptitude area assignment. The results show that if the Army were to cluster jobs into nine job families using a CE method and combine this with FLS assignment instead of their current system (nine operational job families with AA assignment), their estimated average increase in MPP would be .153 representing a 166.3% gain in predicted performance. This MPP gain translates into an improvement worth $280 million dollars per year. The results in Table 29 also show that even if the Army were to keep their current nine operational job families but change to FLS assignment using the full ASVAB, their estimated average increase in MPP would be .122 representing a 132.6% gain in predicted performance. This MPP gain translates into an improvement worth $224 million dollars per year.

In summary, this section demonstrated that many of the statistically significant differences among the MPP scores also represented substantial practical improvements in MPP. Some of the greatest improvements come from increasing the number of job families and from using FLS instead of aptitude area assignment. Zeidner and Johnson (1989b) predicted that use of FLS assignment would provide the greatest improvements in MPP scores with the second greatest improvements occurring by increasing the number of job families. They estimated that increasing the number of job families would provide a 50% improvement above the benefits from FLS assignment. In fact, the current study results suggest that this figure is actually much greater. If the Army were to utilize the best condition from Design A of this study (i.e., a CE

clustering method to increase their number of job families to 12, the full set of experimental predictors, and FLS assignment) there would be a 71.3% improvement in MPP compared to the use of the current 9 operational job families, the ASVAB, and FLS assignment. If the Army were to utilize the best condition from Design B of this study (i.e., a CE clustering method to increase their number of job families to 23, the ASVAB, and FLS assignment) there would be a 177% improvement in MPP compared to the use of the current 9 operational job families, the ASVAB, and FLS assignment. These improvements can be translated into added gains ranging from $280 to over $400 million per year over and above the benefits accrued from the addition of FLS assignment procedures.

IV. DISCUSSION AND CONCLUSIONS

A. Implications For DAT

1. Refinement of DAT

Differential assignment theory (DAT) was first proposed by Johnson and Zeidner (1990, 1991) and Johnson, Zeidner, and Scholarios (1990) as the conceptual basis for initiating research and interpreting results from research intended to improve the efficiency, measured in terms of MPP, of a personnel classification system. The concept of DAT is derived from the integrative review of personnel classification literature, with special emphasis on the contributions of Brogden and Horst, combined with the systematic development of methodologies for improving classification efficiency, as described in Johnson and Zeidner (1990, 1991).

Several fundamental concepts form the basic assumptions for DAT. The first and third (as first presented) hold that, in the general case, there is a complex set of principles defining separate approaches for optimizing either the selection or classification procedures. There is an exception for the special situation where FLS composites based on complete information are used as both selection and assignment variables for each job family, each job family consists of a single job, and a LP algorithm is used to optimally and simultaneously select and assign entities to jobs (the MDS algorithm). All deviations from this special situation where the same test composites and job families are optimal for both selection and classification requires that a decision be made as to whether it is desired to maximize the effectiveness of selection or classification.

The second concept of DAT maintains that utility models, where the object is to maximize the benefits less the costs, provides the best approach for evaluating alternative policies and procedures for selection, classification or placement, and assignment of personnel to jobs.

The fourth concept argues that computer technology has reached the state where it is practical to implement any selection and assignment strategy and/or algorithm that can be shown to provide a useful gain in MPP.

Additional basic concepts of DAT could be derived from an examination of the examples of DAT principles provided by Johnson and Zeidner (1990, 1991). For example, it appears that DAT assumes a non-trivial degree of multidimensionality in the joint predictor-criterion (JP-C) space despite the inevitable presence of a strong general cognitive ability factor, "g", and the high level of credibility of several other validity generalization concepts often associated with the traditional general factor theorists. It should be emphasized that there is no inconsistency between DAT and validity generalization theory as originated by Mosier (1951) or the more recent literature on validity generalization as it pertains to selection efficiency or the utility of selection.

DAT provides a basis for optimism in that it argues for the feasibility of designing, developing, and implementing personnel classification and assignment systems far superior to the existing operational systems. We believe that most operational classification systems developed or modified since 1980 were designed and/or evolved in the pessimistic belief that the dimensionality in the JP-C space was small (even to the point of unidimensionality) and that the weights utilized in FLS composites lacked adequate stability to permit the design of an effective personnel classification system. Thus, the optimistic belief that efficient personnel classification is attainable is also an attribute of DAT.

Several DAT principles are supported by the results of this study. The principles confirmed include: (1) the effectiveness of using FLS composites as assignment variables (AVs) in place of unit weighted composites designed to maximize predictive validity; (2) the increase in MPP as the number of job families is increased; and (3) the further increase in MPP as improved job family structure raises FLS composite validities and reduces FLS composite intercorrelations.

The findings of this study will be integrated with those of a number of companion studies to further refine the basic concepts and principles of DAT. For example, in the present study we did not anticipate the extent to which validities were increased by a job clustering algorithm designed to sustain the average differential validity remaining in the set of job families as jobs were agglutinated into the desired number of job families. We were similarly surprised, in a companion study in which we did not anticipate the smallness of the gain in MPP attributable

to the differing validities of a single predictor across jobs. Each of these studies has both confirmed and enriched DAT.

2. Implementation of DAT

Several DAT principles are supported by the results of this study. These findings point to very high potential benefits obtainable from a major overhaul of the Army's selection and classification system. An effective redesign of this system should start with the acceptance of the maximization of MPP as an over arching objective.

The design of an effective selection and classification system requires the consideration of many practical issues outside the scope of DAT. Tradition and perceived necessity provide a number of entrenched solutions to operational problems concerned with matching job preferences of recruits, distribution of personnel across MOS to meet quality standards, providing vocational opportunities for females, minorities and underprivileged recruits, and the use of unit (or at least positive) weights for the tests in AVs. We believe DAT would considerably impact on a reconsideration of many policy issues. Although this study is not directly focused on these issues, we recognize that the full implementation of the results of this study requires the reconsideration of these policies.

Zeidner and Johnson (1989b, 1991b) predicted that use of FLS composites instead of AAs could increase the potential MPP obtainable from a classification system by 100 percent. The present study confirms this prediction by showing that the gain obtainable from optimizing AVs is 133 percent -- if initial assignments could be accomplished using an LP algorithm without consideration of individual preferences. We still lack information as to the effect that a concerted effort to persuade recruits to accept suitable assignments (i.e., assignments to jobs in which their predicted performance is relatively high) would have on recruiting costs. Until recently many thought that very little utility was lost through permitting preferences (often based on no information, or worse, serious misinformation about Army jobs) to be the primary determinant of initial assignments. Evidence in this and related studies show that a great deal of utility is lost through failure to make more use of optimal assignment information.

B. Operational Implications

1. Broad Conclusions

Our data provide compelling evidence that the existing operational test composites could be reconstituted to substantially improve classification efficiency. The evidence also strongly supports the usefulness of the existing ASVAB as a classification tool. The percentage gain obtainable from adding all 20 of the Project A experimental measures to the existing tests of the ASVAB is a 31 percent increase in classification efficiency. A 299 percent gain over the operational job families and composites is achieved by using FLS composites, optimal assignment, 12 CE job families, and the experimental Project A measures.

The 31 percent gain from adding new Project A tests is substantial when compared to the gains obtainable from making changes, one at a time, to the same baseline condition used to compute this gain. If we use FLS composites for 9 operational job families as our baseline (MPP = .214), we show a gain of 31 percent by only adding the 20 experimental tests, a gain of 15 percent by only changing to 9 job families based on empirical clustering, and a gain of 14 percent by changing to 12 job families based on empirical clustering.

A number of general conclusions can be drawn by examining these comparative gains. First, we see a higher classification efficiency inherent in the ASVAB than is usually posited. Second the failure to obtain even higher differential gains from the addition of new experimental variables to the ASVAB probably reflects the relative lack of emphasis given to classification efficiency by test development researchers over the past two decades. Third, the total gain of 299 percent achieved by implementing all of our proposed changes in the operational system, including the additional differential validity provided by Project A experimental tests, reflects a potential that cannot presently be fully realizable in an operational system constrained by current policies, but definitely points to a route that should eventually lead to very substantial gains in MPP.

While the procedures used to form the existing operational job families are clearly not optimal, they are much more effective than are the corresponding AA composites. Even the Career Management Field (CMF) clusters provide considerable improvement in classification efficiency when used to expand the number of job families to which assignment is accomplished.

It would appear that job families which meet other administrative and training requirements apart from personnel classification, such as CMF, can be effectively utilized in a personnel classification system.

The authors of the principle technical report on Project A (McLaughlin et al., 1984) concluded that an empirical job clustering process was inherently ineffective because of its dependence on presumed unstable regression weights used to form assignment variables (AVs). The findings of the present study, however, show that even when sampling error is allowed to take its full toll, the MPP obtainable in independent samples is greatly improved by the use of empirical clustering of jobs into families and the representation of these families by FLS composites.

A major reconstitution of the job families in the Army's classification system should be based on all available validity data, as well as on information available from job analyses. We do not wish to suggest that the job family structure decisions should be based on the limited data utilized in the present methodological study. However, we are confident that the major conclusions of this study will be confirmed as additional data are collected and analyzed using simulations to obtain MPP values.

2. Policy Issues

A number of policy issues pertaining to personnel classification and assignment must be resolved before a new system incorporating DAT concepts and principles can be implemented. A number of these issues are noted below.

a. The "g" Controversy. Does the poor classification efficiency available from the existing operational AAs mean that the Army should, as some validity generalization proponents contend, change to a system which uses a single measure of cognitive ability, plus measures of psychomotor ability and clerical speed?

b. The Feasibility of Implementing LP Algorithms. Can optimal assignment algorithms be implemented in the current recruiting market? If not, can cut scores be raised in such a way as to provide a similar level of MPP?

c. Using FLS Composites as AVs. Can FLS composites with both positive and negative weights be implemented? If not, can a comparably effective two-tiered strategy, in which the second tier uses composites with all positive weights, be implemented?

d. The Substitution of "g" For AFQT. Can a general FLS composite be substituted for AFQT as the selection instrument?

e. Quality Distribution. Can quality distribution policies be altered to use predicted performance instead of AFQT as the measure of personnel quality?

f. Optimal Simultaneous Selection And Assignment. Must the Army continue to use a two-stage selection and classification system in which selection and classification is accomplished in separate successive stages, instead of the more effective and equitable single stage system in which selection and classification is accomplished simultaneously? Such a single stage algorithm is described by Johnson and Zeidner (1990, 1991). It is called the multidimensional screening (MDS) algorithm. Future plans to make use of MDS should affect the choice of a job clustering algorithm for the design of a new system.

g. Assessing Future Requirements. Can the quality requirements of future weapon systems be assessed in terms of FLS composites or factor composites used in the second tier instead of through the use of AFQT?

C. Accomplishing Operational Changes

1. Options for the CE Job Clustering Algorithm

We believe our CE clustering algorithm and the FORTRAN program implementing this algorithm to be a major product of this study. The flexibility built into this algorithm for including additional options adds to its value. There are a number of options which we believe would add to the usefulness of this algorithm for making changes in operational classification systems.

We first describe an earlier, untested, concept that had a number of features relevant to the operational use of a job clustering algorithm. We then describe additional features we believe have practical value in the reconstitution of operational job families, and describe how these features could be provided as options to our CE clustering algorithm.

A classification-efficient job clustering method which was considered, but not selected for implementation in the present study, has two stages. Kernels, consisting of one or more

jobs, for a desired number of job families are selected during the first stage. In stage 2, the remaining jobs are then distributed to one of these kernels (established job families) in such a way as to maximize H_d. Since MOS selected to initially define a family (that is, the kernel) remain in that family throughout the clustering process without being immersed (agglutinated) into any other family, we believe this second stage would be particularly applicable to the refinement of operational job families.

For Design A, the initial 6 (or 9, or 12) job families were to be identified as the set of 6 (or 9, or 12) MOS, out of the 18 MOS in the data, which as a set of job families (one job to a family) would yield the highest value for H_d. Applying this concept to an operational situation the initial (kernel) job families would instead be provided by a small number of MOS which, based on all available information, appear to be located near the center of job families which span the joint predictor-criterion space (with as much distance between the kernels as can be obtained). It may be desirable to include other career management considerations in the decision process that yields the set of kernels.

The adding of further jobs to the job family kernels is accomplished sequentially, with all unassigned jobs on which adequate data is available being considered during each cycle of the algorithm. Only one unassigned job is selected for inclusion in a job family during each cycle. The job making the greatest overall contribution to H_d by being agglutinated into that family becomes a member of that family, and the remaining unassigned jobs then become candidates for selection in the succeeding cycles.

Our CE job clustering algorithm would have more use in the redesign of operational job families if the algorithm was modified to provide two additional options, each permitting one or more alternative approaches to the forming of job families. The first of these options is sufficient to accomplish the job clustering objectives of the alternative algorithm (considered but not programmed and tested) described above. The two options together permit an efficient use of our CE algorithm for clustering jobs into a set of families in which no families lack sufficient validity data to provide for stable regression weights in the corresponding FLS composites.

Without modifying our CE algorithm we could incorporate a designated set of jobs into prescribed job families to form the kernels of job families that are desired for administrative reasons or, based on prior data and experience, are judged to have similar aptitude requirements.

We could then use our unaltered CE algorithm, as applied in this study, but we would probably prefer to use our algorithm with one or both of the proposed options.

Option one adds the capability of designating some jobs or job families as ineligible for agglutination with each other. These designated families are prevented, by option one, from losing their identity through being agglutinated with each other or with families containing more than a stipulated number of jobs.

Option two requires a stipulated sample size for the validity data associated with each family resulting from the agglutination of a pair of jobs and/or job families. The implementation of this option in our algorithm can be accomplished during the examination of the D matrix in each cycle. As the elements in each D matrix are examined (searching for the smallest cell value) for selecting the pair of jobs and/or job families that would be most appropriate for agglutination, the combined N associated with each cell of D is tested and a cell is not considered for selection unless the combined N of the associated pair exceeds the prescribed N.

The preferred procedure for using this option would be to first, as stage 1, obtain a solution (a set of job families) using the unaltered CE clustering algorithm. An F matrix in which the rows represent the job families obtained in this initial solution, with those families based on inadequately sized validity samples shredded into their constituent jobs, is then constructed. In stage 2, this revised F matrix is then used as input to the CE clustering algorithm with both the first and second options activated. The succeeding cycles of stage 2, in accordance with option 1, would then agglutinate the remaining jobs with each other or with the job families retained from stage 1. Since, in accordance with option 2, only the individual jobs and the specified job families now (after stage 1) have large enough validity samples to be eligible for agglutination, the jobs cannot be agglutinated with each other and are instead distributed among the job families identified in stage 1 in such a way as to maximize H_d/m. The end result would be a set of job families in which all the job families have adequate validity data to permit the forming of stable AVs, while using the proven efficiency of our CE clustering algorithm for providing a high value of H_d.

<u>2. Redesigning the Personnel Classification System</u>

Zeidner and Johnson (1989b, 1991b) proposed a sequence of changes in the design of operational systems for the selection, classification and initial assignment of new personnel.

They assumed that the adoption of the use of FLS composites as AVs was the source of the largest potential increase in MPP, and probably the easiest to incorporate in an operational system. The present study shows that the reconstitution of job families by increasing both the quantity and quality of job families used in the classification process, can provide a comparable gain in MPP.

The results of this study support the conclusion that an increase in the number of job families for classification purposes would be economically profitable even if the structure of the sets of families has been created for some other purpose such as career ladder management or management of training. The immediate increase in number of job families, in conjunction with improved aptitude area composites for each family, could greatly increase the MPP resulting from the classification process. This expected increase is so great that we are less certain than we once were that the shredding out of the nine Army job families should await the adoption of FLS composites as AVs.

The four methodological studies concerned with the measurement and improvement of classification efficiency suggested in Zeidner and Johnson (1989), plus two additional ones in process of being initiated, should be completed by the GWU research team prior to 1993. We fully expect that DAT will be extensively expanded and refined by then and the operational methodology available for the redesign of selection and classification systems will also be expanded, validated, better described, and better understood than at present. Research now in progress on related topics such as synthetic validity should add to the improvement of technology on personnel classification. We are hopeful that we will see the start of a new era in which personnel classification receives the attention it deserves.

We believe the gains in MPP afforded by the CE algorithm for the formation of job families evaluated in this study are great enough to justify future use of this algorithm as a research tool when further validity data are acquired. We also believe this algorithm should be used to provide one source of information to be combined with judgment in the formulation of operational job families.

While synthetic validity might appropriately be used in the context of predictive validity for designing a selection system, it is always inappropriate to substitute predictive validity concepts for MPP in the formulation of personnel classification systems. Synthetic validity

might correctly be viewed as one source of validity information required to implement the MPP focused techniques demonstrated in this study.

The implementation of an ideal operational classification system is unlikely to be accomplished in a single step. Traditions relating to Army classification systems and the administrative complexities involved in implementing changes inhibit making one overall major change in the operational classification system incorporating all desired improvements. We believe changes are most likely to occur in a number of separate steps:

1. Substitute FLS-ASVAB composites for the existing AAs as the AVs for the existing 9 job families.

2. Increase the number of job families and corresponding AVs using judgment to adjust the existing CMF boundaries.

3. Construct improved SQT-type job knowledge measures for a comprehensive set of MOS and obtain scores for two years of recruit input after soldiers have been on the job for 6 to 8 months.

4. Develop classification-efficient families and corresponding AVs to substitute for the a priori job families (while retaining the large number of job families).

5. Eliminate use of job families and instead use separate AVs for each job in the initial assignment process (first tier); use a smaller number of job families, one for each factor score, in the second tier.

Steps 1 and 2

The first two steps should be accomplished through the use of all available research data for the computation of FLS-ASVAB composites. The FLS composites should be used to provide both AA scores for inclusion in the soldier's record and recommended classification to job families at the time of initial assignment. When the number of job families exceeds 20, installation of a two-tiered classification system should be considered. The first tier provides for initial assignment and makes use of FLS composites. Composite scores for initial assignment are computed within a figurative black box and the test weights are invisible to the examinees and transparent to the personnel administration staff. The second tier uses a smaller number of factor composites, covering the same joint predictor-criterion space; factor scores are recorded

in official records and are intended for subsequent use by individuals and counselors to assist in making career decisions.

Step 3

The principal obstacle to an immediate application of the results of this study to the redesign of an operational system may be the low credibility of SQT when used as a criterion variable and the limited number of MOS covered in the Project A concurrent validation study. To the extent that the utility obtainable from the implementation of the findings of the Design B components of this study are dependent on the credibility of SQT as a personnel research criterion variable, the value of obtaining validity data covering an equivalent number of MOS, but using a more credible technical proficiency measure, would be well worth the cost. Approaches for extrapolating validity information from a relatively small set of jobs to the entire set of MOS in the Army, such as the use of synthetic validity methods, also require validities for a large number of MOS before a credible validation of the approach can be provided. A major finding of this study is that the benefits obtainable from such a collection of criterion scores would far surpass the estimated costs.

Both the McLaughlin et al. (1984) study and the present study show that there is a significant content difference between SQT and other criterion variables. It is obvious that SQT does not measure the same thing as either school grades or the Core Technical Proficiency (CTP) criterion of the Project A concurrent validation study. Unfortunately, we lack a more "ultimate" criterion that could be used to establish the superiority of one or another of these three criteria. Judging from their psychometric properties and the objectives that guided their construction, we believe that most measurement specialists would readily agree that the CTP criterion is best and school grades the worst for purposes of both research and operational developments of the type described here. Traditional SQT items are intended to have training diagnostic applicability, although less representative of the job and otherwise inappropriate as a predictor of on-the-job performance. These items are also frequently intended to be criterion referenced, guaranteeing poor discriminability among those who are at least minimally qualified. However, it would not be difficult to develop additional test items with more appropriate psychometric properties and content. These additional items could be administered at the same time as the traditional SQT items. It should be possible to minimize the difference between the

content of these additional items and that of the CTP measures for the half of the MOS included in the concurrent study of Project A that lack "hands on" items.

We emphasize that the development of a superior classification system requires information about predictor and criterion variables for a large number of representative MOS. While we do not reject the usefulness of using all existing data in conjunction with analytic and judgmental data concerning MOS to accomplish an interim reconstitution of job families and AVs, we believe any resulting system eventually should be validated using a credible CTP-type criterion measure. A simulation that concludes with the computation of MPP of individuals or entities after optimal assignment to jobs would, of course, be required.

Step 4

We recommend the use of the techniques of this study for designating the MOS that form job families and for identifying corresponding AVs, to form a first tier classification system. This can be done when it is felt that adequate validity information exists. We believe policy makers should seriously consider the parallel installation of a second tier in the classification system for use in making career decisions. Important research results bearing on the design of a two-tiered system will be available prior to 1992.

The results of this study indicate that the classification-efficient clustering method developed and described here is more than adequate, and is without doubt the best of those known to us for use in obtaining the job families for the first tier in a personnel classification system. However, other classification- efficient job clustering methods also have potential for use in future efforts to reconstitute job families, particularly for the second tier. For example, rotation of CE factors in the JP-C space to simple structure may provide classification-efficient job families and corresponding AVs useful for counseling soldiers and the setting of minimum standards that are visible to all. Such a factorial approach is effective for producing job families that are no more numerous than twice the number of factors; a family can be identified by each end (positive and minus ends) of each factor. Thus, the factorial approach is not a good source of larger numbers of job families. However, a smaller set of job families may serve the needs of counselors better than a larger set.

Zeidner and Johnson (1989b, 1991b) have proposed a two-tiered system which would use a large number of job families for initial assignment and a smaller set for counseling and other administrative needs. The study exploring this issue, one that is in progress at GWU, will emphasize a factor analytic approach in which classification-efficient factors rotated to simple structure in the joint predictor-criterion space will provide factor scores for use as AVs.

Step 5

DAT predicts that an optimal classification system can be obtained when a separate AV is used for each MOS that has some minimum amount of validity information. We do not know what validity sample size is required to provide this minimum. It seems reasonable that when only very small samples are available, judgment may be more important than empirical data for use in both job clustering and the definition of an AV for each cluster. When samples are a little larger, but still small, the validity information provided by similar MOS might be combined to provide an alternative to sheer judgment.

The use of a small number of broadly defined families cannot fail to have at least as many MOS closer to one or more of the family boundaries than to the center of the job cluster where the FLS composite for that family is most representative. There is no theoretical basis for believing that the expected distribution of the points representing MOS in a multidimensional joint predictor-criterion (JP-C) space is anything other than rectangular (evenly distributed). Assuming such a distribution of points in a JP-C space with 6 dimensions (a 6 space), even a family located in a multidimensional corner would still have a greater probability of being closer to one or more of the hyperplanes separating it from the other families than to the center of its own family. Families located nearer to the center of the space will have an even greater probability of being located on, or near, a boundary. An MOS located near a boundary between two families cannot be expected to have classification efficiency with respect to that pair of jobs.

A promising alternative approach to placing MOS into broad job families calls for the computation of separate FLS composites for each job. Instead of clustering jobs into fixed families, a separate cluster is formed around each MOS. Each such job cluster centered on a selected MOS would have adequate validity data to provide stable FLS composites for the job which forms the nucleus of each such cluster. The investigation of such an approach would be an appropriate next step in continued research on the reconstitution of Army MOS into job

families. The model sampling techniques and computer software utilized in this study, both of which are now in the public domain, would require only minor modifications to permit their use in the execution of such a study.

The optimal use of synthetic validity techniques also provides a promising means of using available validity data to establish FLS composites for all but the least populated MOS. The job families and AVs resulting from the use of synthetic validities should be evaluated in terms of MPP computed in the context of system simulations of the type used in this study.

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APPENDIX A: JOB SAMPLE

TABLE A-1: Military Occupational Specialty (MOS) Sample Sizes for Both the Project A and "McLaughlin" Data Sets

MOS	Name	Project A n	McLaughlin n
11B	Infantryman	491	6355
12B	Combat Engineer	544	3109
13B	Cannon Crewmember	464	6575
16S	MANPADS Crewmember	338	596
19E	M48-M60 Armor Crewmember	394	3297
27E	TOW/DRAGON Repairer	123	363
31C	Single Channel Radio Operator[a]	289	2393
54E	NBC Specialist	340	113
55B	Ammunition Specialist	203	288
63B	Light Wheel Vehicle Mechanic	478	1495
64C	Motor Transport Operator	507	3681
67N	Utility Helicopter Repairer	238	511
71L	Administrative Specialist	427	2824
76W	Petroleum Supply Specialist	339	664
76Y	Unit Supply Specialist	444	1149
91A	Medical Specialist	392	783
94B	Food Service Specialist	368	3943
95B	Military Police	597	4516
	Average Sample Size	388	2370

[a]MOS 31C was designated as 05C Radio Teletype Operator in the McLaughlin 1981/1982 data set.

TABLE A-2: Military Occupational Specialty (MOS) Sample Sizes for all 60 Jobs in "McLaughlin" Data Set

MOS	n	MOS	n
*05C Radio TT Operator	2393	73C Finance Specialist	688
05H Elec War/SIGINT INTER_IMC	171	74D Computer/Tape Writer	132
*11B Infantryman	6355	74F Programmer/Analyst	95
11C Indirect Fire Infmn	1494	75B Personnel Admin Sp	1061
11H HV Anti-Armor Wpn Infn	979	76C Eq Rec & Parts Sp	331
*12B Combat Engineer	3109	76V Mat Stor & Hdlg Sp	216
12C Bridge Crewman	450	*76W Petroleum Supply Sp	664
12F Engineer Tracked Crmn	151	*76Y Unit Supply Sp	1149
*13B Cannon Crmn (TK4)	6575	82C Field Artillery Surveyor	434
13E Cannon Fire Direction Sp	627	*91B Medical Specialist	783
13F Fire Support Sp	693	91E Dental Specialist	203
15D Lance Crmb/MLRS Sgt	281	91P X-Ray Specialist	159
*16S MANPADS Crewmember	596	92B Medical Lab Sp	310
19D Cavalry Scout	1249	93H Air Traffic Con Tower Op	114
*19E M48-M60 Armor Crmn	3297	*94B Food Service Sp	3943
*27E TOW/Dragon Rep	363	*95B Military Police	4516
27F Vulcan Repairer	130	96B Intelligence Analyst	218
31M Multichannel Comm Eq Op	2482	98C Elec War/SIGINT Analyst	186
31N Tactical Ckt Con	189		
31V Tac Comm Sysop/Mech	515	* = Design A MOS	
36C Wire Sys Inst/Op	499	Average	1002
43E Parachute Rigger	100		
52D Power Generation Equip Rep	178		
*54E NBC Specialist	113		
*55B Ammunition Sp	288		
57H Cargo Specialist	272		
62B Construction Equip Rep	233		
62E HV Const Equip Rep	202		
62F Lifting/Loading Eq Op	129		
*63B Lt Wh Veh/Pwr Gen Mech	1495		
63H Track Veh Repairer	335		
63N M60A1/A3 Tank Sys Mech	286		
63W Wheel Veh Mechanic	180		
*64C Motor Transport Op	3681		
*67N Utility Hel Repairer	511		
67V OBN/Scout Hel Rep	294		
68G Aircraft Structural Rep	125		
68J Aircraft FC Repairer	148		
*71L Administrative Sp	2824		
71M Chapel Activities Sp	182		
71N Traffic Mgmt Coordinator	163		
72E Combat Telecom Center Op	569		

(continued)

APPENDIX B: PREDICTOR MEASURES

TABLE B-1: ASVAB/Project A Experimental Predictors and Reliabilites

Code	Predictors	Reliability[a]
	ASVAB tests[b]	
GS	General Science	0.86
AR	Arithmetic Reasoning	0.91
NO	Numerical Operations	0.78
CS	Coding Speed	0.85
AS	Auto Shop Information	0.87
MK	Mathematical Knowledge	0.87
MC	Mechanical Comprehension	0.85
EI	Electronics Information	0.82
PC	Paragraph Comprehension	0.81
WK	Word Knowledge	0.92
	Paper-and-pencil spatial composite[c]	
SPAT	Spatial Composite	0.71
	Perceptual-psychomotor composites[d]	
CPAC	Complex perceptual accuracy composite	0.62
CPSP	Complex perceptual speed composite	0.95
NMSA	Number speed and accuracy composite	0.84
PSYM	Psychomotor composite	0.82
SRAC	Simple reaction accuracy composite	0.52
SRSP	Simple reaction speed composite	0.88
	Job orientation composites (JOB)[e]	
AUTO	Autonomy composite	0.50
SUPP	Organizational and Co-Worker Support	0.67
ROUT	Routine composite	0.46
	Temperament and biodata composites (ABLE)[f]	
ADJU	Adjustment composite	0.74
DEPN	Dependability composite	0.76
COND	Physical condition composite	0.85
SURG	Achievement orientation composite	0.78
	Interest composites (AVOICE)[f]	
AUDI	Audiovisual interest composite	0.74
COMB	Combat interest composite	0.78
FSER	Food service interest composite	0.67
PSER	Protective service interest composite	0.76
TECH	Technical interest composite	0.75
MACH	Machinery interest composite	0.79

[a] ASVAB reliabilities reported in McLaughlin, et al. (1984), p.9; Project A reliabilities reported in Campbell (1988).
[b] Tests PC and WK are combined to form VE, a more general verbal ability test.
[c] Test-retest reliability (N=468 to 487)
[d] Odd-even reliability
[e] Internal consistency reliability (alpha)
[f] Test-retest reliabilities (N=368 to 412)

TABLE B-2: Army AFQT Composite and Aptitude Area Composites

Code	Composite	ASVAB Test Formula
AFQT	Armed Forces Qualification Test	AR + NO/2 + VE
CL	Clerical	VE + NO + CS
CO	Combat	CS + AR + MC + AS
EL	Electronics Repair	AR + MK + EI + GS
FA	Field Artillery	CS + AR + MC + MK
GM	General Maintenance	MK + EI + GS + AS
MM	Mechanical Maintenance	NO + EI + MC + AS
OF	Operators/Food	NO + VE + MC + AS
SC	Surveillance and Communications	NO + CS + VE + AS
ST	Skilled Technical	VE + MK + MC + GS

Source: Maier and Grafton (1981)

APPENDIX C: RELIABILITIES FOR "MCLAUGHLIN" DATA SET

TABLE C-1: Cronbach Alpha Reliability Estimates Across Three Years for the SQT Criterion

MOS	n	Reliability 1987 Alpha	n	Reliability 1988 Alpha	n	Reliability 1989 Alpha	n
*05C Radio TT Operator	2393	0.86	5660	0.82	4827	0.75	4504
05H Elec War/SIGINT INTER_IMC	171	0.83	591	0.77	461	0.67	450
*11B Infantryman	6355	0.88	22332	0.88	22329	0.86	23596
11C Indirect Fire Infmn	1494	0.89	3138	0.88	3679	0.88	4805
11H HV Anti-Armor Wpn Infn	979	0.87	1237	0.86	2331	0.78	2627
*12B Combat Engineer	3109	0.81	6944	0.85	6733	0.86	6511
12C Bridge Crewman	450	0.75	974	0.82	1083	0.79	1109
12F Engineer Tracked Crmn	151	0.89	299	0.86	429	0.87	376
*13B Cannon Crmn (TK4)	6575	0.82	5163	0.83	5812	0.83	6944
13E Cannon Fire Direction Sp	627	0.87	833	0.86	1431	0.89	1234
13F Fire Support Sp	693	0.78	1253	0.86	1275	0.84	1339
15D Lance Crmb/MLRS Sgt	281	0.90	945				
*16S MANPADS Crewmember	596	0.76	1231	0.77	1467		
19D Cavalry Scout	1249	0.87	2555	0.87	1947	0.87	1233
*19E M48-M60 Armor Crmn	3297	0.87	1121	0.87	2952	0.79	83
*27E TOW/Dragon Rep	363	0.70	194	0.74	279	0.88	225
27F Vulcan Repairer	130	0.73	98	0.84	106	0.90	131
31M Multichannel Comm Eq Op	2482	0.86	3440	0.86	4543	0.76	4215
31N Tactical Ckt Con	189	0.88	196	0.86	196	0.81	336
31V Tac Comm Sysop/Mech	515	0.86	2602	0.80	1519	0.69	1954
36C Wire Sys Inst/Op	499	0.88	524				
43E Parachute Rigger	100	0.91	568	0.86	571	0.89	1008
52D Power Generation Equip Rep	178	0.85	3157	0.85	2260		
*54E NBC Specialist	113	0.79	1490				
*55B Ammunition Sp	288	0.86	1486	0.88	1582	0.86	1623
57H Cargo Specialist	272	0.75	851				
62B Construction Equip Rep	233	0.84	1385	0.90	1959	0.88	1950
62E HV Const Equip Rep	202	0.84	1166	0.79	1353	0.84	1503
62F Lifting/Loading Eq Op	129	0.82	457	0.83	424	0.80	426
*63B Lt Wh Veh/Pwr Gen Mech	1495	0.81	8184	0.83	4559	0.88	7863
63H Track Veh Repairer	335	0.88	1535	0.84	1651	0.87	1537
63N M60A1/A3 Tank Sys Mech	286	0.79	743		250	0.79	255
63W Wheel Veh Mechanic	180	0.87	2434	0.86	2404	0.85	2501
*64C Motor Transport Op	3681	0.87	10359				
*67N Utility Hel Repairer	511	0.86	1122	0.76	758	0.77	1056
67V OBN/Scout Hel Rep	294	0.80	1031	0.91	1085	0.78	1130
68G Aircraft Structural Rep	125	0.86	681	0.83	510	0.89	468
68J Aircraft FC Repairer	148	0.89	267	0.88	294	0.91	499
*71L Administrative Sp	2824	0.82	7576	0.85	7940	0.85	6928
71M Chapel Activities Sp	182	0.82	785	0.87	854	0.84	749
71N Traffic Mgmt Coordinator	163			0.82	982	0.67	972
72E Combat Telecom Center Op	569	0.90	2107	0.86	1555	0.82	1914

(continued)

MOS	n	Reliability 1987 Alpha	n	Reliability 1988 Alpha	n	Reliability 1989 Alpha	n
73C Finance Specialist	688	0.82	1601	0.80	1704	0.79	1695
74D Computer/Tape Writer	132	0.77	750				
74F Programmer/Analyst	95	0.75	419				
75B Personnel Admin Sp	1061	0.81	1956	0.80	2548	0.72	2604
76C Eq Rec & Parts Sp	331	0.75	3500	0.81	3957	0.75	3497
76V Mat Stor & Hdlg Sp	216	0.78	3591	0.73	3964	0.70	3490
*76W Petroleum Supply Sp	664			0.85	4574	0.78	5052
*76Y Unit Supply Sp	1149	0.87	6917	0.89	7629	0.85	6903
82C Field Artillery Surveyor	434	0.85	762	0.83	498	0.82	684
*91B Medical Specialist	783	0.85	8172	0.81	10363	0.79	10499
91E Dental Specialist	203	0.86	831	0.86	969	0.83	1075
91P X-Ray Specialist	159	0.86	380	0.91	522	0.83	729
92B Medical Lab Sp	310	0.88	837	0.91	1067	0.87	1081
93H Air Traffic Con Tower Op	114	0.87	208				
*94B Food Service Sp	3943	0.82	7131	0.82	8422	0.77	7607
*95B Military Police	4516	0.81	9250	0.80	9218	0.80	10980
96B Intelligence Analyst	218	0.75	418	0.74	429	0.72	563
98C Elec War/SIGINT Analyst	186	0.69	481	0.70	161	0.75	377
Average	1002	0.83	2688	0.83	2893	0.81	3018

* = Design A MOS

APPENDIX D: POPULATION DATA

TABLE D-1: 1980 Youth Population ASVAB Intercorrelations (see Appendix B for code names)

	GS	AR	NO	CS	AS	MK	MC	EI	VE
GS	1.00	.72	.52	.45	.64	.69	.70	.76	.80
AR	.72	1.00	.63	.51	.53	.83	.69	.66	.73
NO	.52	.63	1.00	.70	.30	.62	.40	.41	.62
CS	.45	.51	.70	1.00	.22	.52	.34	.34	.57
AS	.64	.53	.30	.22	1.00	.41	.74	.75	.52
MK	.69	.83	.62	.52	.41	1.00	.60	.59	.70
MC	.70	.69	.40	.34	.74	.60	1.00	.74	.60
EI	.76	.66	.41	.34	.75	.59	.74	1.00	.67
VE	.80	.73	.62	.57	.52	.70	.60	.67	1.00

Source: Personal Communication from Lawrence M. Hanser, ARI Chief, Selection and Classification Tech. Area to Jesse Orlansky, Institute for Defense Analyses, 13 July, 1988

TABLE D-2: Population Predictor Intercorrelations (see Appendix B for code names)

PREDICTORS 1-12

	GS	AR	NO	CS	AS	MK	MC	EI	VE	SPAT	CPAC	CPSP
GS	1.0000	0.7200	0.5200	0.4500	0.6400	0.6900	0.7000	0.7600	0.8000	0.6707	0.3166	0.3170
AR	0.7200	1.0000	0.6300	0.5100	0.5300	0.8300	0.6900	0.6600	0.7300	0.7301	0.3560	0.2876
NO	0.5200	0.6300	1.0000	0.7000	0.3000	0.6200	0.4000	0.4100	0.6200	0.5162	0.3047	0.3119
CS	0.4500	0.5100	0.7000	1.0000	0.2200	0.5200	0.3400	0.3400	0.5700	0.4877	0.3155	0.2953
AS	0.6400	0.5300	0.3000	0.2200	1.0000	0.4100	0.7400	0.7500	0.5200	0.5677	0.2084	0.2427
MK	0.6900	0.8300	0.6200	0.5200	0.4100	1.0000	0.6000	0.5900	0.7000	0.6802	0.3485	0.2811
MC	0.7000	0.6900	0.4000	0.3400	0.7400	0.6000	1.0000	0.7400	0.6000	0.7413	0.2775	0.3005
EI	0.7600	0.6600	0.4100	0.3400	0.7500	0.5900	0.7400	1.0000	0.6700	0.6159	0.2749	0.2617
VE	0.8000	0.7300	0.6200	0.5700	0.5200	0.7000	0.6000	0.6700	1.0000	0.6234	0.3678	0.2783
SPAT	0.6707	0.7301	0.5162	0.4877	0.5677	0.6802	0.7413	0.6159	0.6234	1.0000	0.3886	0.4057
CPAC	0.3166	0.3560	0.3047	0.3155	0.2084	0.3485	0.2775	0.2749	0.3678	0.3886	1.0000	-0.2025
CPSP	0.3170	0.2876	0.3119	0.2953	0.2427	0.2811	0.3005	0.2617	0.2783	0.4057	-0.2025	1.0000
NMSA	0.5895	0.7156	0.6966	0.5545	0.3938	0.6774	0.4914	0.4996	0.6498	0.6143	0.3000	0.4129
PSYM	0.4459	0.4383	0.3249	0.2920	0.4586	0.3841	0.5479	0.4544	0.3773	0.6040	0.2477	0.3768
SRAC	0.2136	0.2179	0.1653	0.1703	0.1901	0.1861	0.2100	0.2023	0.2312	0.2311	0.2284	0.0642
SRSP	0.2169	0.2283	0.2646	0.2534	0.1385	0.2146	0.1892	0.1766	0.2288	0.2569	0.0695	0.3716
AUTO	0.2486	0.2261	0.1849	0.1562	0.2227	0.1953	0.2203	0.2393	0.2602	0.2039	0.0566	0.1009
SUPP	0.1383	0.1196	0.1739	0.1745	0.0436	0.1294	0.0584	0.0938	0.2090	0.0978	0.0886	0.0516
ROUT	-0.3150	-0.3021	-0.2525	-0.2355	-0.2507	-0.2620	-0.2898	-0.2737	-0.3420	-0.2974	-0.1429	-0.1408
ADJU	0.2256	0.2399	0.1925	0.1338	0.2048	0.2147	0.2261	0.2259	0.2315	0.2258	0.1227	0.1186
DEPN	0.0522	0.1017	0.1350	0.1520	-0.0384	0.1450	0.0162	0.0330	0.0889	0.0561	0.1070	-0.0034
COND	-0.0462	-0.0322	-0.0048	-0.0387	-0.0147	-0.0269	-0.0123	-0.0348	-0.0556	-0.0352	-0.0547	0.0688
SURG	0.2076	0.2533	0.2371	0.2020	0.1593	0.2393	0.1903	0.2003	0.2392	0.2023	0.1246	0.0997
AUDI	0.0147	0.0022	0.0058	0.0221	-0.0909	0.0482	-0.0184	-0.0171	0.0507	0.0032	0.0199	0.0052
COMB	0.1539	0.0660	-0.0309	-0.0663	0.3433	0.0120	0.2594	0.2220	0.0435	0.1737	0.0135	0.0728
FSER	-0.2097	-0.1852	-0.1295	-0.1199	-0.2366	-0.1408	-0.2317	-0.2179	-0.1939	-0.2148	-0.0924	-0.1278
PSER	-0.0990	-0.1426	-0.1365	-0.1275	0.0101	-0.1601	-0.0577	-0.0580	-0.1356	-0.0907	-0.0818	0.0008
TECH	-0.0039	0.0629	0.1116	0.0783	-0.1353	0.1275	-0.0575	-0.0342	0.0483	-0.0134	0.0601	-0.0156
MACH	-0.1545	-0.1908	-0.2822	-0.2951	0.1864	-0.2210	0.0465	0.0075	-0.2955	-0.0620	-0.1171	-0.0538

TABLE D-2 (CONT.): Population Predictor Intercorrelations

PREDICTORS 13-24

	NMSA	PSYM	SRAC	SRSP	AUTO	SUPP	ROUT	ADJU	DEPN	COND	SURG	AUDI
GS	0.5895	0.4459	0.2136	0.2169	0.2486	0.1383	-0.3150	0.2256	0.0522	-0.0462	0.2076	0.0147
AR	0.7156	0.4383	0.2179	0.2283	0.2261	0.1196	-0.3021	0.2399	0.1017	-0.0322	0.2533	0.0022
NO	0.6966	0.3249	0.1653	0.2646	0.1849	0.1739	-0.2525	0.1925	0.1350	-0.0048	0.2371	0.0058
CS	0.5545	0.2920	0.1703	0.2534	0.1562	0.1745	-0.2355	0.1338	0.1520	-0.0387	0.2020	0.0221
AS	0.3938	0.4586	0.1901	0.1385	0.2227	0.0436	-0.2507	0.2048	-0.0384	-0.0147	0.1593	-0.0909
MK	0.6774	0.3841	0.1861	0.2146	0.1953	0.1294	-0.2620	0.2147	0.1450	-0.0269	0.2393	0.0482
MC	0.4914	0.5479	0.2100	0.1892	0.2203	0.0584	-0.2898	0.2261	0.0162	-0.0123	0.1903	-0.0184
EI	0.4996	0.4544	0.2023	0.1766	0.2393	0.0938	-0.2737	0.2259	0.0330	-0.0348	0.2003	-0.0171
VE	0.6498	0.3773	0.2312	0.2288	0.2602	0.2090	-0.3420	0.2315	0.0889	-0.0556	0.2392	0.0507
SPAT	0.6143	0.6040	0.2311	0.2569	0.2039	0.0978	-0.2974	0.2258	0.0561	-0.0352	0.2023	0.0032
CPAC	0.3000	0.2477	0.2284	0.0695	0.0566	0.0886	-0.1429	0.1227	0.1070	-0.0547	0.1246	0.0199
CPSP	0.4129	0.3768	0.0642	0.3716	0.1009	0.0516	-0.1408	0.1186	-0.0034	0.0688	0.0997	0.0052
NMSA	1.0000	0.4413	0.1983	0.3023	0.1890	0.1497	-0.2577	0.2093	0.0990	0.0062	0.2301	-0.0293
PSYM	0.4413	1.0000	0.1434	0.2696	0.1371	0.0528	-0.2091	0.1934	-0.0230	0.0990	0.1352	-0.0224
SRAC	0.1983	0.1434	1.0000	0.1200	0.0368	0.0561	-0.0919	0.0694	0.0245	-0.0456	0.0498	-0.0241
SRSP	0.3023	0.2696	0.1200	1.0000	0.0681	0.0635	-0.1225	0.1149	0.0250	0.0477	0.0991	-0.0152
AUTO	0.1890	0.1371	0.0368	0.0681	1.0000	0.2877	-0.1530	0.1069	0.0051	0.0531	0.2010	0.1033
SUPP	0.1497	0.0528	0.0561	0.0635	0.2877	1.0000	-0.2384	0.1163	0.2542	0.0584	0.3358	0.1682
ROUT	-0.2577	-0.2091	-0.0919	-0.1225	-0.1530	-0.2384	1.0000	-0.1912	-0.0363	-0.0653	-0.2435	-0.0059
ADJU	0.2093	0.1934	0.0694	0.1149	0.1069	0.1163	-0.1912	1.0000	0.3414	0.2268	0.6038	0.0622
DEPN	0.0990	-0.0230	0.0245	0.0250	0.0051	0.2542	-0.0363	0.3414	1.0000	0.1279	0.5971	0.1924
COND	0.0062	0.0990	-0.0456	0.0477	0.0531	0.0584	-0.0653	0.2268	0.1279	1.0000	0.3410	0.0622
SURG	0.2301	0.1352	0.0498	0.0991	0.2010	0.3358	-0.2435	0.6038	0.5971	0.3410	1.0000	0.1838
AUDI	-0.0293	-0.0224	-0.0241	-0.0152	0.1033	0.1682	-0.0059	0.0622	0.1924	0.0622	0.1838	1.0000
COMB	0.0276	0.2522	0.0092	0.0196	0.1373	0.0294	-0.0808	0.1666	-0.0298	0.1537	0.1868	0.1781
FSER	-0.1650	-0.2282	-0.0718	-0.1014	-0.0944	-0.0527	0.2245	-0.0707	0.0489	-0.0341	-0.0412	0.3074
PSER	-0.1145	0.0214	-0.0293	-0.0071	0.0002	0.0635	0.0482	0.0392	0.0340	0.1304	0.0790	0.1378
TECH	0.0688	-0.0316	-0.0292	0.0116	0.0684	0.2415	0.0084	0.1489	0.3069	0.0869	0.2955	0.6719
MACH	-0.2163	0.0616	-0.0653	-0.0809	0.0138	-0.0697	0.1119	0.0014	-0.1022	0.1296	0.0076	0.2014

PREDICTORS 25-29

	COMB	FSER	PSER	TECH	MACH
GS	0.1539	-0.2097	-0.0990	-0.0039	-0.1545
AR	0.0660	-0.1852	-0.1426	0.0629	-0.1908
NO	-0.0309	-0.1295	-0.1365	0.1116	-0.2822
CS	-0.0663	-0.1199	-0.1275	0.0783	-0.2951
AS	0.3433	-0.2366	0.0101	-0.1353	0.1864
MK	0.0120	-0.1408	-0.1601	0.1275	-0.2210
MC	0.2594	-0.2317	-0.0577	-0.0575	0.0465
EI	0.2220	-0.2179	-0.0580	-0.0342	0.0075
VE	0.0435	-0.1939	-0.1356	0.0483	-0.2955
SPAT	0.1737	-0.2148	-0.0907	-0.0134	-0.0620
CPAC	0.0135	-0.0924	-0.0818	0.0601	-0.1171
CPSP	0.0728	-0.1278	0.0008	-0.0156	-0.0538
NMSA	0.0276	-0.1650	-0.1145	0.0688	-0.2163
PSYM	0.2522	-0.2282	0.0214	-0.0316	0.0616
SRAC	0.0092	-0.0718	-0.0293	-0.0292	-0.0653
SRSP	0.0196	-0.1014	-0.0071	0.0116	-0.0809
AUTO	0.1373	-0.0944	0.0002	0.0684	0.0138
SUPP	0.0294	-0.0527	0.0635	0.2415	-0.0697
ROUT	-0.0808	0.2245	0.0482	0.0084	0.1119
ADJU	0.1666	-0.0707	0.0392	0.1489	0.0014
DEPN	-0.0298	0.0489	0.0340	0.3069	-0.1022
COND	0.1537	-0.0341	0.1304	0.0869	0.1296
SURG	0.1868	-0.0412	0.0790	0.2955	0.0076
AUDI	0.1781	0.3074	0.1378	0.6719	0.2014
COMB	1.0000	0.0864	0.3913	0.1905	0.5881
FSER	0.0864	1.0000	0.1708	0.3518	0.2269
PSER	0.3913	0.1708	1.0000	0.2216	0.3364
TECH	0.1905	0.3518	0.2216	1.0000	0.2118
MACH	0.5881	0.2269	0.3364	0.2118	1.0000

TABLE D-3: Corrected Validity Coefficients for 18 MOS for Project A Data with CTP Criterion

PREDICTORS 1-9

	GS	AR	NO	CS	AS	MK	MC	EI	VE
11B	0.656866	0.621229	0.536789	0.463335	0.483873	0.634964	0.545002	0.565734	0.634258
12B	0.683895	0.623335	0.482641	0.354050	0.574970	0.612381	0.612354	0.668390	0.659945
13B	0.422443	0.380366	0.333044	0.275551	0.435487	0.329572	0.419501	0.390942	0.400737
16S	0.493229	0.531860	0.403993	0.399331	0.327244	0.539718	0.400081	0.419077	0.493532
19E	0.599531	0.550098	0.428410	0.348390	0.491584	0.561922	0.535999	0.522067	0.548541
27E	0.660288	0.620168	0.632819	0.561978	0.520991	0.571064	0.552572	0.611584	0.654890
31C	0.477411	0.544064	0.306164	0.186036	0.370263	0.533522	0.453222	0.468237	0.436274
54E	0.577282	0.620872	0.443222	0.409187	0.500734	0.594605	0.550117	0.571048	0.549027
55B	0.481222	0.419575	0.366245	0.358299	0.377841	0.372635	0.453166	0.417673	0.543057
63B	0.461438	0.403683	0.215213	0.245279	0.580193	0.353725	0.549157	0.513533	0.382682
64C	0.300903	0.351512	0.098842	0.075076	0.379292	0.314629	0.377936	0.350880	0.226409
67N	0.398259	0.390994	0.249866	0.200611	0.361391	0.399703	0.398365	0.403935	0.363369
71L	0.451731	0.523196	0.374147	0.332497	0.224830	0.561851	0.351650	0.338491	0.473435
76W	0.724902	0.677280	0.415595	0.470868	0.693884	0.632991	0.705073	0.693100	0.684616
76Y	0.573827	0.607247	0.420033	0.400435	0.445024	0.635650	0.491260	0.558312	0.577437
91A	0.466726	0.457812	0.379704	0.439253	0.390980	0.475335	0.406133	0.403509	0.432202
94B	0.550727	0.682143	0.523106	0.496724	0.399889	0.618427	0.475801	0.464941	0.617696
95B	0.308507	0.361463	0.312987	0.275644	0.221359	0.365255	0.268593	0.297468	0.317382

PREDICTORS 10-17

	SPAT	CPAC	CPSP	NMSA	PSYM	SRAC	SRSP	AUTO
11B	0.652374	0.365831	0.315400	0.534503	0.402093	0.226193	0.233807	0.228662
12B	0.622855	0.309670	0.227002	0.512925	0.372447	0.190950	0.204843	0.227686
13B	0.490541	0.280079	0.218420	0.370732	0.325088	0.129346	0.221210	0.241487
16S	0.539057	0.327187	0.161110	0.491465	0.412220	0.116820	0.117623	0.091227
19E	0.589534	0.366108	0.231046	0.515206	0.372504	0.201491	0.191977	0.147325
27E	0.522335	0.295617	0.277979	0.582803	0.410929	0.178950	0.162618	0.159222
31C	0.449896	0.272000	0.086412	0.403564	0.262090	0.084207	0.097554	0.067000
54E	0.603960	0.318320	0.248402	0.511470	0.379777	0.226676	0.138062	0.173768
55B	0.510010	0.311239	0.134092	0.361530	0.408399	0.204356	0.145157	0.093111
63B	0.518942	0.161082	0.235836	0.310585	0.359398	0.180705	0.167438	0.214925
64C	0.396216	0.219718	0.189678	0.285677	0.256463	0.150450	0.112552	0.161223
67N	0.451617	0.202696	0.058565	0.306593	0.283747	0.082735	0.048330	0.080653
71L	0.524502	0.369656	0.159688	0.416152	0.275218	0.189140	0.159404	0.084238
76W	0.717186	0.321605	0.339029	0.595906	0.486608	0.379508	0.164464	0.191275
76Y	0.541140	0.322173	0.166824	0.562101	0.247266	0.241203	0.208201	0.130668
91A	0.508260	0.207015	0.193966	0.415018	0.316744	0.124493	0.172211	0.138501
94B	0.643599	0.458344	0.245147	0.606390	0.323287	0.302815	0.224887	0.200528
95B	0.375857	0.245767	0.104942	0.327871	0.238337	0.092203	0.079345	0.097684

TABLE D-3 (CONT.): Corrected Validity Coefficients for 18 MOS for Project A Data with CTP Criterion

	PREDICTORS 18-25 SUPP	ROUT	ADJU	DEPN	COND	SURG	AUDI	COMB
11B	0.123723	-0.30512	0.239024	0.152477	-0.01476	0.290709	0.00232	0.184334
12B	0.115598	-0.29492	0.204694	0.063205	-0.01829	0.229732	0.02302	0.170702
13B	0.170646	-0.25147	0.165706	0.040654	-0.02298	0.125694	-0.03220	0.247007
16S	0.262131	-0.24657	0.192076	0.144852	-0.09337	0.197470	0.01368	0.132213
19E	0.147059	-0.31942	0.209132	0.152346	-0.03104	0.221872	0.04348	0.204331
27E	0.128286	-0.23395	0.180262	0.021000	-0.12227	0.170586	-0.11192	0.166848
31C	0.049802	-0.08717	0.108294	0.113786	-0.09517	0.126693	0.11199	0.108130
54E	0.089491	-0.20924	0.227338	0.167239	-0.07412	0.269000	-0.05607	0.105195
55B	0.110772	-0.29471	0.193754	-0.034219	-0.07633	0.152132	-0.05980	0.176590
63B	0.054786	-0.15637	0.193494	0.065594	-0.06677	0.178713	-0.09691	0.304999
64C	0.092326	-0.13812	0.119468	0.069535	-0.04641	0.112791	-0.04330	0.159918
67N	0.062287	-0.17310	0.191400	0.184218	-0.00327	0.211099	0.02633	0.113485
71L	0.096050	-0.20412	0.184007	0.211097	-0.03759	0.256343	0.09834	0.029767
76W	0.185879	-0.34674	0.273591	0.123225	-0.09744	0.305606	0.00774	0.169576
76Y	0.241912	-0.27059	0.171466	0.148173	-0.09447	0.231602	0.02011	-0.016822
91A	0.184232	-0.15618	0.201112	0.221338	-0.08370	0.237056	0.01486	0.181293
94B	0.211675	-0.25494	0.211309	0.169314	-0.11001	0.253456	0.06162	-0.039677
95B	0.110249	-0.17103	0.159484	0.143164	-0.02086	0.180596	-0.07999	0.022969

	PREDICTORS 26-29 FSER	PSER	TECH	MACH
11B	-0.24569	-0.08846	0.04205	-0.14864
12B	-0.20016	-0.15054	0.02201	-0.07964
13B	-0.13923	-0.04086	-0.03497	0.04404
16S	-0.11756	-0.02380	0.07341	-0.13096
19E	-0.19852	-0.07536	0.11842	-0.06009
27E	-0.20526	-0.23876	-0.03661	-0.08600
31C	-0.03077	-0.07153	0.13561	0.05820
54E	-0.17415	-0.14690	0.01373	-0.07097
55B	-0.13820	-0.13924	-0.06987	-0.00325
63B	-0.18927	-0.09858	-0.10459	0.25888
64C	-0.14868	-0.00988	-0.00728	0.13068
67N	-0.07037	-0.05552	0.06522	-0.03315
71L	-0.10148	-0.02221	0.13728	-0.17941
76W	-0.18391	-0.14190	0.07675	-0.05137
76Y	-0.17607	-0.19286	0.07027	-0.16625
91A	-0.10266	-0.04917	0.04814	-0.00726
94B	-0.02029	-0.12862	0.10869	-0.23578
95B	-0.12993	-0.08489	-0.01798	-0.15076

TABLE D-4: Corrected Validity Coefficients for 18 MOS for "McLaughlin" Data with SQT/Training Criteria

	AR	AS	CS	EI	GS	MC	MK	NO	VE
05C	0.522481	0.466196	0.301145	0.511024	0.500311	0.519526	0.477943	0.327860	0.487276
11B	0.435398	0.359757	0.295275	0.398889	0.430805	0.425119	0.421797	0.328748	0.414520
12B	0.456009	0.421902	0.234617	0.437370	0.424477	0.482489	0.412656	0.296038	0.379036
13B	0.467479	0.429503	0.277034	0.448068	0.464670	0.472093	0.444128	0.335162	0.432633
16S	0.597241	0.602851	0.350482	0.665018	0.619113	0.653891	0.577616	0.402013	0.562170
19E	0.537569	0.503318	0.342678	0.523518	0.559232	0.562900	0.493701	0.399920	0.539033
27E	0.418988	0.275268	0.366791	0.311033	0.372870	0.332871	0.480805	0.416963	0.510881
54E	0.446692	0.348940	0.081376	0.456362	0.320026	0.467917	0.430625	0.287750	0.321035
55B	0.512050	0.324288	0.404777	0.423100	0.460575	0.416224	0.564711	0.408218	0.488787
63B	0.450968	0.479444	0.204551	0.486390	0.417487	0.486575	0.403886	0.276881	0.383260
64C	0.470434	0.436968	0.278294	0.470200	0.451799	0.467933	0.409456	0.309199	0.456755
67N	0.448919	0.425099	0.242493	0.476322	0.441937	0.533555	0.409983	0.240398	0.375627
71L	0.635395	0.327525	0.494356	0.464185	0.552146	0.448577	0.625413	0.517749	0.642766
76W	0.523521	0.510653	0.277521	0.521921	0.536168	0.533771	0.472523	0.286529	0.440204
76Y	0.531108	0.312413	0.431966	0.402779	0.490305	0.416069	0.568753	0.425842	0.507263
91A	0.211951	0.195167	0.178205	0.182522	0.231842	0.219951	0.183240	0.169034	0.195193
94B	0.577372	0.499129	0.349491	0.551992	0.570028	0.537964	0.504077	0.369834	0.563089
95B	0.562539	0.441142	0.378885	0.511458	0.536842	0.502840	0.525118	0.417818	0.537126

NOTE: The validity matrix for all 60 MOS in the "McLaughlin" Data Set is available upon request.

APPENDIX E: REMOVING EFFECTS OF NEGATIVE ROOTS ON PROJECT A VALIDITY MATRIX

Proof that a Matrix Consisting of Column Arrays of Real Numbers Multiplied by Its Transpose Must Have All Positive Eigenvalues

1. Notation:

Y = a rectangular matrix of real numbers; the column arrays should represent test scores with the rows representing individuals.

$\mathbf{M}_y$ = **Y'Y**; every matrix multiplied by its transpose is necessarily a square matrix with all diagonal elements equal to the sums of squares of real numbers and the off diagonal elements equal to cross products that can be either positive or negative real numbers. The diagonal values for non-zero column arrays are, of course, positive numbers.

$\mathbf{M}_w$ = **(YW)' (YW)** = **W'Y'Y W**; Defining **W** as a matrix of weights consisting of real numbers, it is seen that $\mathbf{M}_w$ is also necessarily a square matrix with all diagonal elements equal to either positive real numbers or zeros. The zeros may result from the use of a **W** which transforms some of the columns of **Y** to columns of zeros; the sums of squares of these columns are, of course, zeros.

D = a diagonal matrix of eigenvalues; these are the eigenvalues to which this proof refers.

A = a square eigenvector matrix such that **A'A** = **A A'** = **I**, and **A' (Y'Y) A** = **D**; it is well known that if **Y'Y** is of full rank the latter equation will uniquely exist.

B = a rectangular orthonormal matrix such that **B'B** = **I**, **B'B** is an idempotent matrix, and **B' (Y'Y) B** = **D**; the latter equation is also uniquely defined. When **Y'Y** is not of full rank, the usual situation, this **D** is the matrix of eigenvalues we are interested in proving much be positive numbers when **Y** consists of real numbers.

2. Demonstration:

We see that by definition, assuming that **Y** consists of real numbers, that the diagonal elements of both $\mathbf{M_y}$ and $\mathbf{M_w}$ must all be positive or zero. We further see that setting **W** equal to either **A** or **B**, which ever is appropriate, assures that $\mathbf{M_w}$ is equal to **D**. Thus, all elements of **D** must be positive if the elements of **Y** are real numbers, and we can say that all the eigenvalues of **Y'Y** will necessarily be positive or zero if **Y** is made up of real numbers. If even one of the eigenvalues of the matrix, **M**, are negative we can say with certainty that **M** is not equal to the product of a score matrix (made up of real numbers) and its transpose. That is, **M** cannot equal **Y'Y** for any **Y** defined as above.

3. Implications:

A matrix of raw test and/or performance scores can be first transformed into deviate scores which all have zeros as their column means, and then each column divided by its standard deviation to create standard scores. The resulting matrix **Y** consists of standard scores when considered by columns. Each column has a mean of zero and a standard deviation of one. Obtaining a new **Y** by dividing this intermediate one by the square root of the number of rows yields a matrix for which **Y'Y** yields a matrix of product moment correlation coefficients. Thus, a correlation matrix is one of the $\mathbf{M_y}$ matrices that cannot have a negative eigenvalue, and it can be emphatically stated that an alledged correlation matrix possessing even one negative eigenvalue could not have been computed from a single set of scores obtained from the same sample. Alledged correlation matrices yielding one or more negative eigenvalues can result from many different causes, including: the use of incomplete data to compute some cells, the use of tetrachoric correlation coefficients for some cells, and the combining of the results from several samples to obtain a covariance or correlation matrix. Usually small adjustments to a few cells can provide a corrected correlation matrix which has all positive or zero eigenvalues.

Steps to Remove the Effects of Negative Roots on Project A Validity Matrix (Source: Whetzel, 1991)

1. $V R_t^{-1} V' = C_p$

2. $$\frac{R_t}{V} T_1 = \frac{F_t}{F_v} T_2 = \frac{F_{tp}}{F_p}$$

   where F_p is the principal components solution of C_p
   $T_1 = A_t D_t^{-1/2}$ and T_2 is found by solving $T_2'(F_v'F_v)T_2 = D_2$

3. Delete factors with negative roots from F_p to obtain F_{pk}

4. $V^+ = F_{pk}F_{tp}'$

5. Compute $V^+ R_t^{-1} V^{+\prime} = C_p^+$

APPENDIX F: ANALYSIS SAMPLE GENERATION

I. PROCEDURE FOR GENERATING ANALYSIS SAMPLE

a. Notation

N = number of entities in an MOS sample
n = number of test variables (j=1...29)
m = number of jobs (i=1...18)
R_t = 29x29 matrix of predictor intercorrelations
V = m x 29 matrix of validity coefficients
X_m = N x 30 matrix of random normal deviates for the mth job sample

b. Compute for each of the 18 job samples, 29 synthetic test scores and 1 criterion score using the Gramian factor solution of $R_t v_i$ as the transformation matrix.

b.1 $F_i = R_t v_i \, (A \, D^{-1/2} \, A')$

where,

F_i = 30x30 transformation matrix for the ith job sample

$R_t v_i$ = matrix of 29 test intercorrelations in rows and columns 1-29 plus vectors of 29 validities in 30th row and column for the ith job;

$$\left[\begin{array}{c|c} R_t & v_i \\ \hline v_i & 1.0 \end{array}\right]$$

A = eigenvectors of 30x30 intercorrelation-validity matrix

D = diagonal matrix of eigenvalues of intercorrelation-validity matrix

b.2 $Y_i = X_N \, F_i'$

where,

Y_i = Nx30 matrix of test and criterion scores (with the same expected parameters as the population) for N entities in the ith job sample.

c. Compute matrix of sums-of-squares and cross-products, $Q_i = Y_i' Y_i$, for each job sample.

d. Compute the vector of covariances, C_i, for each job sample.

d.1 Identify q_i, the 30th row of Q_i.

d.2 $m_i = (I' Y_i) 1/N$

where,

m_i = row vector of means of 29 predictors and 1 criteria (1x30)

1 = summing vector of 1s.

d.3 $c_i = (1/N)q_i - (m_{ik}\ m_i)$; and drop the 30th element.
where,
m_{ik} = a scalar which is the 30th element of m_i.
c_i = 1x29 vector of covariances of the predictors

e. Compute analysis sample validity matrix (V_a) using 18 C_is.

e.1 For each job sample, compute validities for 29 predictors: $v_{ai} = (S_i^{-1/2})\ c_i\ (1/s_i)$
where,
v_{ai} = 1x29 vector of validities between 29 predictors and 1 criterion variable for each job sample
S_i = diagonal matrix (taken from Q_i) with the variances of the 29 predictors and 1 job sample criterion in the diagonal
s_i = scalar which is the covariance of the criterion for the ith job sample; it is the 30th element of the matrix S_i

e.2 Assemble 18x29 validity matrix (V_a) for combined job samples using v_{ai}.

$$V_a = (v_{a1}',\ v_{a2}',\ .\ .\ .\ .,\ v_{a18}')'$$

f. Compute analysis sample intercorrelation matrix (R_a)

f.1 Drop criterion variable from 18 Q_is.

f.2 Sum the 18 Q_is weighted by sample size:
$Q_t = {}_{i=1}^{18}\ N_i\ Q_i$

f.3 Compute analysis sample intercorrelation matrix:

a. $m_t = [\ {}_{i=1}^{18}\ N_i(m_i)\ ]\ 1/\ {}_{i=1}^{18}N_i$

b. $C_t = Q_t\ (1/\ {}_{i=1}^{18}\ N_i) - m_t'(m_t)$
where,
C_t = combined covariance matrix for the 18 job samples
Q_t = combined sums-of-squares and cross-products matrix for the 18 job samples

c. $R_a = S^{-1/2}\ C_t\ S^{-1/2}$
where,
S = diagonal matrix of the diagonal elements of C_t (i.e., predictor variables).

TABLE F-1: INITIALIZATION SEEDS USED TO GENERATE MATRIX OF RANDOM NORMAL DEVIATES (X_m) FOR ANALYSIS SAMPLE

X_m for mth MOS sample	Initialization Seed
X1	1587175283
X2	1976274088
X3	1271376363
X4	1728981280
X5	450351973
X6	724467093
X7	2015440489
X8	277105243
X9	68383890
X10	1964442650
X11	135371761
X12	605699282
X13	1656991152
X14	234809644
X15	805238231
X16	399052330
X17	2003666395
X18	1300943904

TABLE F-2: Analysis Sample Predictor Intercorrelations (see Appendix B for code names)

PREDICTORS 1-9

	GS	AR	NO	CS	AS	MK	MC	EI	VE
GS	1.00000	0.71978	0.52743	0.44542	0.64820	0.68728	0.71156	0.76236	0.79520
AR	0.71978	1.00000	0.62800	0.49502	0.54084	0.82568	0.68904	0.65296	0.73448
NO	0.52743	0.62800	1.00000	0.69626	0.32077	0.62096	0.40977	0.41260	0.62451
CS	0.44542	0.49502	0.69626	1.00000	0.22223	0.49864	0.33390	0.33251	0.56959
AS	0.64820	0.54084	0.32077	0.22223	1.00000	0.41681	0.73911	0.75078	0.51914
MK	0.68728	0.82568	0.62096	0.49864	0.41681	1.00000	0.59577	0.57768	0.69993
MC	0.71156	0.68904	0.40977	0.33390	0.73911	0.59577	1.00000	0.73880	0.60463
EI	0.76236	0.65296	0.41260	0.33251	0.75078	0.57768	0.73880	1.00000	0.66455
VE	0.79520	0.73448	0.62451	0.56959	0.51914	0.69993	0.60463	0.66455	1.00000
SPAT	0.67339	0.73280	0.53150	0.49495	0.56744	0.67778	0.73758	0.60739	0.62930
CPAC	0.31255	0.35070	0.29975	0.31894	0.19571	0.33621	0.26699	0.26318	0.36539
CPSP	0.33420	0.30202	0.32794	0.31336	0.25990	0.30185	0.32482	0.27826	0.29779
NMSA	0.59448	0.72021	0.70341	0.55597	0.41169	0.67984	0.50018	0.49857	0.66101
PSYM	0.46243	0.43935	0.34584	0.29845	0.46265	0.37799	0.54713	0.46232	0.38456
SRAC	0.22610	0.21320	0.16104	0.17295	0.19423	0.18480	0.20497	0.20906	0.24201
SRSP	0.23572	0.23633	0.27474	0.26668	0.16228	0.22299	0.20377	0.20315	0.25615
AUTO	0.25845	0.24468	0.20359	0.16786	0.24415	0.20559	0.23501	0.24783	0.28000
SUPP	0.13595	0.12318	0.16773	0.17596	0.04155	0.13357	0.05720	0.09501	0.20500
ROUT	-0.31485	-0.30689	-0.25269	-0.23590	-0.24090	-0.26236	-0.29184	-0.26263	-0.33297
ADJU	0.24471	0.25308	0.20380	0.13960	0.20404	0.23283	0.23388	0.23516	0.23970
DEPN	0.06508	0.09893	0.14136	0.16064	-0.03845	0.15240	0.01137	0.03938	0.10231
COND	-0.04943	-0.02892	-0.00414	-0.03948	-0.02557	-0.02673	-0.00974	-0.04200	-0.05606
SURG	0.22196	0.26116	0.23745	0.20869	0.14966	0.25444	0.18511	0.20147	0.24407
AUDI	0.01454	0.02279	0.01324	0.02628	-0.08044	0.06490	-0.00826	-0.00617	0.05884
COMB	0.15768	0.05750	-0.03191	-0.06616	0.34264	0.00238	0.24480	0.22622	0.03818
FSER	-0.19883	-0.18273	-0.14583	-0.13293	-0.22763	-0.13563	-0.22383	-0.20691	-0.18970
PSER	-0.09213	-0.14403	-0.14491	-0.12370	0.01535	-0.15871	-0.06066	-0.05814	-0.13622
TECH	-0.00629	0.06884	0.11075	0.07234	-0.13633	0.13780	-0.06826	-0.04307	0.05530
MACH	-0.14907	-0.18398	-0.27661	-0.29726	0.18344	-0.21946	0.04437	0.00556	-0.29738

PREDICTORS 10-19

	SPAT	CPAC	CPSP	NMSA	PSYM	SRAC	SRSP	AUTO	SUPP	ROUT
GS	0.67339	0.31255	0.33420	0.59448	0.46243	0.22610	0.23572	0.25845	0.13595	-0.31485
AR	0.73280	0.35070	0.30202	0.72021	0.43935	0.21320	0.23633	0.24468	0.12318	-0.30689
NO	0.53150	0.29975	0.32794	0.70341	0.34584	0.16104	0.27474	0.20359	0.16773	-0.25269
CS	0.49495	0.31894	0.31336	0.55597	0.29845	0.17295	0.26668	0.16786	0.17596	-0.23590
AS	0.56744	0.19571	0.25990	0.41169	0.46265	0.19423	0.16228	0.24415	0.04155	-0.24090
MK	0.67778	0.33621	0.30185	0.67984	0.37799	0.18480	0.22299	0.20559	0.13357	-0.26236
MC	0.73758	0.26699	0.32482	0.50018	0.54713	0.20497	0.20377	0.23501	0.05720	-0.29184
EI	0.60739	0.26318	0.27826	0.49857	0.46232	0.20906	0.20315	0.24783	0.09501	-0.26263
VE	0.62930	0.36539	0.29779	0.66101	0.38456	0.24201	0.25615	0.28000	0.20500	-0.33297
SPAT	1.00000	0.38305	0.41062	0.61824	0.59619	0.21981	0.26627	0.22440	0.09566	-0.29272
CPAC	0.38305	1.00000	-0.20501	0.30353	0.25474	0.24055	0.08598	0.07289	0.10032	-0.15041
CPSP	0.41062	-0.20501	1.00000	0.42550	0.37502	0.06074	0.35994	0.10256	0.04153	-0.13127
NMSA	0.61824	0.30353	0.42550	1.00000	0.44084	0.19430	0.31724	0.20595	0.15041	-0.27015
PSYM	0.59619	0.25474	0.37502	0.44084	1.00000	0.13981	0.28262	0.16027	0.06490	-0.21372
SRAC	0.21981	0.24055	0.06074	0.19430	0.13981	1.00000	0.11849	0.05171	0.05154	-0.09579
SRSP	0.26627	0.08598	0.35994	0.31724	0.28262	0.11849	1.00000	0.07710	0.05247	-0.12173
AUTO	0.22440	0.07289	0.10256	0.20595	0.16027	0.05171	0.07710	1.00000	0.27862	-0.15299
SUPP	0.09566	0.10032	0.04153	0.15041	0.06490	0.05154	0.05247	0.27862	1.00000	-0.24772
ROUT	-0.29272	-0.15041	-0.13127	-0.27015	-0.21372	-0.09579	-0.12173	-0.15299	-0.24772	1.00000
ADJU	0.22158	0.09515	0.13258	0.21836	0.19990	0.07677	0.14092	0.12526	0.10806	-0.20918
DEPN	0.04447	0.09187	0.00438	0.09911	-0.02457	0.01941	0.03227	0.00744	0.25074	-0.05688
COND	-0.03273	-0.04344	0.04337	-0.00360	0.10637	-0.06069	0.02220	0.05974	0.07655	-0.08549
SURG	0.19479	0.11215	0.11621	0.22610	0.12887	0.05397	0.10666	0.19722	0.34122	-0.26958
AUDI	0.01702	0.03381	0.01624	-0.01681	-0.02126	-0.00584	-0.01819	0.09742	0.17444	-0.00857
COMB	0.14999	-0.01369	0.08413	0.02551	0.24652	0.00801	0.01637	0.16565	0.02968	-0.06994
FSER	-0.21667	-0.09562	-0.11637	-0.17283	-0.22699	-0.07272	-0.09337	-0.10740	-0.04133	0.20022
PSER	-0.09294	-0.08502	0.01028	-0.11166	0.01389	-0.00095	-0.00098	-0.00419	0.07959	0.05027
TECH	-0.01612	0.05277	-0.00688	0.07134	-0.04281	-0.03367	0.00136	0.07628	0.25116	-0.00017
MACH	-0.06805	-0.13882	-0.03936	-0.22019	0.06004	-0.07074	-0.08230	0.03570	-0.06237	0.12232

TABLE F-2 (CONT.): Analysis Sample Predictor Intercorrelations

Predictors 20-29

	ADJU	DEPN	COND	SURG	AUDI	COMB	FSER	PSER	TECH	MACH
GS	0.24471	0.06508	-0.04943	0.22196	0.01454	0.15768	-0.19883	-0.09213	-0.00629	-0.14907
AR	0.25308	0.09893	-0.02892	0.26116	0.02279	0.05750	-0.18273	-0.14403	0.06884	-0.18398
NO	0.20380	0.14136	-0.00414	0.23745	0.01324	-0.03191	-0.14583	-0.14491	0.11075	-0.27661
CS	0.13960	0.16064	-0.03948	0.20869	0.02628	-0.06616	-0.13293	-0.12370	0.07234	-0.29726
AS	0.20404	-0.03845	-0.02557	0.14966	-0.08044	0.34264	-0.22763	0.01535	-0.13633	0.18344
MK	0.23283	0.15240	-0.02673	0.25444	0.06490	0.00238	-0.13563	-0.15871	0.13780	-0.21946
MC	0.23388	0.01137	-0.00974	0.18511	-0.00826	0.24480	-0.22383	-0.06066	-0.06826	0.04437
EI	0.23516	0.03938	-0.04200	0.20147	-0.00617	0.22622	-0.20691	-0.05814	-0.04307	0.00556
VE	0.23970	0.10231	-0.05606	0.24407	0.05884	0.03818	-0.18970	-0.13622	0.05530	-0.29738
SPAT	0.22158	0.04447	-0.03273	0.19479	0.01702	0.14999	-0.21667	-0.09294	-0.01612	-0.06805
CPAC	0.09515	0.09187	-0.04344	0.11215	0.03381	-0.01369	-0.09562	-0.08502	0.05277	-0.13882
CPSP	0.13258	0.00438	0.04337	0.11621	0.01624	0.08413	-0.11637	0.01028	-0.00688	-0.03936
NMSA	0.21836	0.09911	-0.00360	0.22610	-0.01681	0.02551	-0.17283	-0.11166	0.07134	-0.12019
PSYM	0.19990	-0.02457	0.10637	0.12887	-0.02126	0.24652	-0.22699	0.01389	-0.04281	0.06004
SRAC	0.07677	0.01941	-0.06070	0.05398	-0.00585	0.00802	-0.07273	-0.00096	-0.03368	-0.07074
SRSP	0.14092	0.03227	0.02220	0.10666	-0.01819	0.01637	-0.09337	-0.00098	0.00136	-0.08230
AUTO	0.12526	0.00744	0.05974	0.19722	0.09742	0.16565	-0.10740	-0.00419	0.07628	0.03570
SUPP	0.10806	0.25074	0.07655	0.34122	0.17444	0.02968	-0.04133	0.07959	0.25116	-0.06237
ROUT	-0.20918	-0.05688	-0.08549	-0.26958	-0.00857	-0.06994	0.20022	0.05027	-0.00017	0.12232
ADJU	1.00000	0.33293	0.22715	0.60838	0.04989	0.16496	-0.08336	0.03047	0.12820	-0.00922
DEPN	0.33293	1.00000	0.13667	0.59075	0.20251	-0.04367	0.06396	0.03126	0.31410	-0.10894
COND	0.22715	0.13667	1.00000	0.34333	0.07349	0.15782	-0.04547	0.13498	0.10826	0.14244
SURG	0.60838	0.59075	0.34333	1.00000	0.17266	0.17082	-0.04036	0.07756	0.28651	-0.00400
AUDI	0.04989	0.20251	0.07349	0.17266	1.00000	0.17159	0.31729	0.13361	0.67286	0.19789
COMB	0.16496	-0.04367	0.15782	0.17082	0.17159	1.00000	0.09267	0.38155	0.17102	0.57606
FSER	-0.08336	0.06396	-0.04547	-0.04036	0.31729	0.09267	1.00000	0.16751	0.35184	0.23177
PSER	0.03047	0.03126	0.13498	0.07756	0.13361	0.38155	0.16751	1.00000	0.20934	0.34614
TECH	0.12820	0.31410	0.10826	0.28651	0.67286	0.17102	0.35184	0.20934	1.00000	0.19457
MACH	-0.00922	-0.10894	0.14244	-0.00400	0.19789	0.57606	0.23177	0.34614	0.19457	1.00000

TABLE F-3: Analysis Sample Validity Coefficients for 18 MOS

PREDICTORS 1-9

	GS	AR	NO	CS	AS	MK	MC	EI	VE
11B	0.616324	0.562951	0.473442	0.383062	0.468460	0.562460	0.477467	0.519798	0.600048
12B	0.674561	0.591346	0.530004	0.329280	0.589070	0.607769	0.627996	0.693098	0.649865
13B	0.407003	0.290783	0.239132	0.199683	0.444174	0.240448	0.402179	0.413035	0.388540
16S	0.532369	0.564768	0.392423	0.399841	0.312493	0.551154	0.415636	0.349667	0.474066
19E	0.643871	0.566385	0.452945	0.324618	0.526622	0.567517	0.613683	0.566852	0.583430
27E	0.687531	0.657306	0.664267	0.530909	0.572547	0.640832	0.561024	0.626965	0.659186
31C	0.538728	0.587352	0.348889	0.158829	0.461669	0.572805	0.472554	0.573544	0.475890
54E	0.575748	0.644649	0.396164	0.392442	0.538695	0.593120	0.541257	0.558782	0.561591
55B	0.501583	0.426438	0.364091	0.390143	0.338015	0.412250	0.414435	0.442930	0.585551
63B	0.478853	0.414483	0.280681	0.292236	0.565156	0.362594	0.541182	0.497081	0.418200
64C	0.311752	0.375835	0.100337	0.134280	0.410017	0.339482	0.397166	0.368794	0.264535
67N	0.416102	0.415564	0.310853	0.220211	0.424643	0.422864	0.464800	0.470580	0.401287
71L	0.466161	0.571514	0.441537	0.371583	0.224624	0.610297	0.376136	0.361487	0.550738
76W	0.745418	0.715050	0.457936	0.523495	0.706044	0.669409	0.725134	0.723530	0.718848
76Y	0.535583	0.558070	0.422517	0.366543	0.417376	0.581944	0.428227	0.509820	0.543894
91A	0.495820	0.486555	0.335059	0.416737	0.409915	0.506523	0.428372	0.408871	0.420976
94B	0.609311	0.734807	0.631953	0.567449	0.401812	0.658941	0.518803	0.521831	0.678982
95B	0.304223	0.411412	0.302817	0.305440	0.254008	0.370947	0.292374	0.289180	0.313460

APPENDIX G: CLASSIFICATION-EFFICIENT PROGRAM

```
C-----------------------------------------------------------C
C PROGRAM:  CLASSIFICATION-EFFICIENT CLUSTERING PROGRAM     C
C PURPOSE:  CLUSTER JOBS INTO 6, 9, OR 12 JOB FAMILIES      C
C           WHILE MAXIMIZING HORST'S DIFFERENTIAL INDEX     C
C-----------------------------------------------------------C
C
C * FUNCTIONS AND SUBROUTINES APPEAR FIRST IN THE PROGRAM
C
C * SUBROUTINE THAT INCREASES THE ROW DESIGNATORS AS NEEDED
      SUBROUTINE CHECK(X, Y, MAX)
      INTEGER X, Y, MAX
      IF (X .LE. (MAX-1)) THEN
         IF (Y .GT. MAX) THEN
            X = X + 1
            Y = X + 1
            END IF
         END IF
      RETURN
      END
C * SUBROUTINE THAT LOCATES THE SMALLEST VALUE IN D MATRIX
      SUBROUTINE LOCATE(D, X, SMLCOL, SMLROW)
      REAL D
      DIMENSION D(18,18)
      INTEGER X, I, J, SMLCOL, SMLROW
      SMLCOL = 1
      SMLROW = 1
      DO 20 I = 1,X
         DO 19 J = 2,X
            IF (D(I,J) .LT. D(SMLROW, SMLCOL)) THEN
               SMLCOL = J
               SMLROW = I
               END IF
19          CONTINUE
20       CONTINUE
      RETURN
      END
C-------------------------------------------------------C
C  MAIN PROGRAM                                         C
C-------------------------------------------------------C
C * DECLARE VARIABLES
      REAL F, K TEMP, C, G, GT, MULT, TOTAL, GGT, DG, M, SUM, HD
      REAL A, SQ, S, B, D, N1, N2
      DIMENSION F(18,32), C(18), G(18,18), GT(18,18), GGT(18,18)
      DIMENSION DG(18), M(18), A(18,18), B(18,18), D(18,18)
      INTEGER NUMCLS, X, Y, NC, I, J, NUM, Q, L, P, R1, R2
      INTEGER SCOL, SROW, S1, S2, Z, R, T
      CHARACTER*8 SOURCE
C * VARIABLES THAT WILL NEED TO BE CHANGED FOR EACH CONDITION
C * NUMBER OF CLUSTERS (6, 9, 12)
      NUMCLS = 6
C * DATA SOURCE (PROJA29, PROJA9, MCGL)
      SOURCE = 'MCGL'
C * NUMBER OF JOBS (ROWS)
      X = 18
C * NUMBER OF FACTORS--COLUMNS IN F MATRIX (9 OR 18)
      Y = 9
C * VALUE AFTER CALCULATION OF 18 CHOOSE 2
      NC = 153
C * READ IN DATA
      IF (SOURCE .EQ. 'PROJA29') THEN
         READ (5,20) ((F(I,J), J=1,18), I=1,18)
20       FORMAT (18(1X,F9.6))
         END IF
      IF ((SOURCE .EQ. 'PROJA9') .OR. (SOURCE .EQ. 'MCGL')) THEN
         READ (5,28) ((F(I,J), J=1,9), I=1,18)
28       FORMAT (9(1X,F9.6))
         END IF
C * ZERO OUT SPACES AT END OF EACH ROW OF THE F MATRIX
      DO 35 I = 1,18
```

```
          DO 34 J = (Y+1), (Y+14)
             F(I,J) = 0
34        CONTINUE
35     CONTINUE
C * ADD COUNTER AND JOB DESIGNATORS TO THE END OF THE ROWS
C      OF THE F MATRIX
       K = 0
       DO 40 I = 1,18
           K = K + 1.0
           F(I,(Y+1)) = 1.0
           F(I,(Y+2)) = K
40     CONTINUE
C * WRITE OUT ORIGINAL F MATRIX TO CHECK PROGRAM
       WRITE (6,41)
41     FORMAT (/1X, 'THE ORIGINAL F MATRIX IS:')
       WRITE (6,43) ((F(I,J), J=1,9), I=1,18)
43     FORMAT (9(1X,F9.6))
C * SET COUNTER TO TRACK THE NUMBER OF CLUSTERS
       NUM = X
C * SET COUNTER FOR THE NUMBER OF ITERATIONS
C * Q IS THE TOTAL NUMBER OF ITERATIONS
       Q = X - NUMCLS + 1
C * CALCULATE COLUMN MEANS OF F MATRIX--STORE IN C VECTOR
C * THE SAME COLUMN MEANS OF F WILL BE USED THROUGHOUT THE PROGRAM
       DO 50 I = 1,Y
          TEMP = 0
          DO 45 J = 1,NUM
             TEMP = TEMP + F(J,I)
45        CONTINUE
          C(I) = TEMP/NUM
50     CONTINUE
       WRITE (6,52)
52     FORMAT (/1X, 'COLUMN MEANS OF F MATRIX')
       WRITE (6,54) (C(I), I=1,Y)
54     FORMAT (9(1X,F6.3))
C * BEGIN LARGE LOOP OF THE PROGRAM
       DO 450 L = 1,Q
C * ZERO OUT VECTORS
          DO 60 I = 1,X
             DG(I) = 0
             M(I) = 0
60        CONTINUE
C * ZERO OUT MATRICES
          DO 65 I = 1,X
             DO 64 J = 1,X
                G(I,J) = 0
                GT(I,J) = 0
                GGT(I,J) = 0
                A(I,J) = 0
                B(I,J) = 0
                D(I,J) = 0
64           CONTINUE
65        CONTINUE
C * WRITE OUT ITERATION NUMBER
          WRITE (6,85)
85        FORMAT (/1X, 'ITERATION NUMBER:')
          WRITE (6,87) L
87        FORMAT (I2)
C * CALCULATE G MATRIX OF DEVIATIONS (VALUE IN EACH COLUMN MINUS
C * ITS COLUMN MEAN)
          DO 100 I = 1,Y
             DO 95 J = 1,NUM
                G(J,I) = (F(J,I) - C(I))
95           CONTINUE
100       CONTINUE
C          WRITE (6,110)
C 110        FORMAT (/1X, 'G MATRIX OF DEVIATIONS')
C          WRITE (6,112) ((G(I,J), J=1,Y), I=1,NUM)
C 112        FORMAT (9(1X,F9.6))
C * TRANSPOSE G MATRIX
          DO 120 I = 1,NUM
             DO 119 J = 1,Y
                GT(J,I) = G(I,J)
```

```
119         CONTINUE
120      CONTINUE
C * CALCULATE GG'
         DO 150 I = 1,NUM
            DO 149 P = 1,NUM
               TOTAL = 0
               DO 140 J = 1,Y
                  MULT = G(I,J) * GT(J,P)
                  TOTAL = TOTAL + MULT
140            CONTINUE
            GGT(I,P) = TOTAL
149         CONTINUE
150      CONTINUE
C * FORM DG VECTOR FROM DIAGONAL ELEMENTS OF GGT
         DO 180 I = 1,NUM
            DG(I) = GGT(I,I)
180      CONTINUE
         WRITE(6,181)
181      FORMAT (/1X, 'DG VECTOR')
         WRITE(6,183) (DG(I), I=1,NUM)
183      FORMAT (18(1X,F6.3))
C * CREATE A VECTOR CONTAINING NUMBER OF JOBS (M) IN EACH FAMILY
C * TO BE USED IN SUBSEQUENT MULTIPLICATIONS
         DO 185 I = 1,NUM
            M(I) = F(I,(Y+1))
185      CONTINUE
         WRITE(6,186)
186      FORMAT (/1X, 'M VECTOR')
         WRITE(6,188) (M(I), I=1,NUM)
188      FORMAT (18(1X,F5.3))
C * CALCULATE HORST'S DIFFERENTIAL INDEX
         SUM = 0
         DO 190 I = 1,NUM
            SUM = SUM + (DG(I) * M(I))
190      CONTINUE
         HD = SUM
         WRITE (6,195)
195      FORMAT (/1X, 'HORST INDEX')
         WRITE (6,197) HD
197      FORMAT (1X, F9.6)
C
C * STOP PROGRAM ON LAST ITERATION SO THAT HD IS CALCULATED BUT
C *  NOTHING ELSE IS DONE
C
         IF (L .EQ. Q) GO TO 500
C
C * CALCULATE "A" MATRIX
         R1 = 1
         R2 = R1 + 1
         DO 250 I = 1,NC
            TOTAL = 0
            CALL CHECK(R1,R2,NUM)
            TOTAL = (M(R1) * DG(R1)) + (M(R2) * DG(R2))
            A(R1,R2) = TOTAL
            A(R2,R1) = TOTAL
            A(R1,R1) = 1.0
            R2 = R2 + 1
250      CONTINUE
         A(NUM,NUM) = 1.0
         WRITE (6,260)
260      FORMAT (/1X, 'A MATRIX')
         WRITE (6,262) ((A(I,J), J=1,X), I=1,X)
262      FORMAT (18(1X,F6.3))
C * CALCULATE "B" MATRIX
         R1 = 1
         R2 = R1 + 1
         DO 290 I = 1,NC
            TOTAL = 0
            SQ = 0
            DO 280 J = 1,Y
               CALL CHECK(R1,R2,NUM)
               S = (((M(R1)*F(R1,J))+(M(R2)*F(R2,J)))/(M(R1)+M(R2)))
     +               - C(J)
```

```
              SQ = S * S
              TOTAL = TOTAL + SQ
280        CONTINUE
           B(R1,R2) = TOTAL * (M(R1) + M(R2))
           B(R2,R1) = TOTAL * (M(R1) + M(R2))
           B(R1,R1) = 0
           R2 = R2 + 1
290     CONTINUE
        WRITE (6,295)
295     FORMAT (/1X, 'B MATRIX')
        WRITE (6,297) ((B(I,J), J=1,X), I=1,X)
297     FORMAT (18(1X,F6.3))
C * CALCULATE (A-B) TO GET A D MATRIX
        DO 320 I = 1,NUM
           DO 319 J = 1,NUM
              D(I,J) = A(I,J) - B(I,J)
319        CONTINUE
320     CONTINUE
        WRITE (6,325)
325     FORMAT (/1X, 'D MATRIX')
        WRITE (6,327) ((D(I,J), J=1,X), I=1,X)
327     FORMAT (18(1X,F6.3))
C * LOCATE SMALLEST VALUE IN D MATRIX
        CALL LOCATE(D,NUM,SCOL,SROW)
        WRITE (6,340)
340     FORMAT (/1X, 'THE SMALLEST VALUE IN D IS IN COLUMN:')
        WRITE (6,343) SCOL
343     FORMAT (1X, I2)
        WRITE (6,345)
345     FORMAT (1X, 'AND ROW:')
        WRITE (6,343) SROW
C * CALCULATE WEIGHTED AVERAGE FOR THE NEW ROW OF F MATRIX
        DO 380 J = 1,Y
           N1 = F(SROW, (Y+1))
           N2 = F(SCOL, (Y+1))
           F(SROW,J) = ((N1*F(SROW,J)) + (N2*F(SCOL,J)))/(N1+N2)
380     CONTINUE
C * STORE JOB DESIGNATORS AT END OF APPROPRIATE F MATRIX ROW
        S1 = INT(N1)
        S2 = INT(N2)
        Z = Y + 1
        P = S1 + 1
        DO 390 R = 1,S2
           F(SROW, (Z+P)) = F(SCOL, (Z+R))
           P = P + 1
390     CONTINUE
C * INCREMENT N COUNTER IN THE COMBINED ROW OF F MATRIX
        F(SROW,Z) = N1 + N2
C * CLOSE REMAINING ROWS TOGETHER IN THE F MATRIX
        T = NUM - SCOL
        DO 400 I = 1,T
           DO 398 J = 1,(Y+14)
              F(SCOL,J) = F((SCOL+1),J)
398        CONTINUE
           SCOL = SCOL + 1
400     CONTINUE
        WRITE (6,410)
410     FORMAT (/1X, 'F MATRIX')
        IF ((SOURCE .EQ. 'PROJA9') .OR. (SOURCE .EQ. 'MCGL')) THEN
          WRITE (6,412) ((F(I,J), J=1,22), I=1,(NUM-1))
412       FORMAT (22(1X,F5.2))
          ENDIF
        IF (SOURCE .EQ. 'PROJA29') THEN
          WRITE (6,416) ((F(I,J), J=19,31), I=1,(NUM-1))
416       FORMAT (13(1X,F5.2))
          ENDIF
C * SET VALUES FOR NEXT ITERATION
        NUM = NUM - 1
        NC = NC - NUM
450   CONTINUE
C * WRITE OUT FINAL F MATRIX
500   WRITE (6,501)
501   FORMAT (/1X, 'FINAL F MATRIX AND JOB CLUSTERS')
```

```
      WRITE (6,510) ((F(I,J), J=1,22), I=1,NUMCLS)
510   FORMAT (22(1X,F5.2))
512   STOP
      END
```

APPENDIX H: SELECTION-EFFICIENT CLUSTERING PROGRAM

```
C-----------------------------------------------------C
C PROGRAM:  SELECTION-EFFICIENT CLUSTERING PROGRAM     C
C PURPOSE:  CLUSTER JOBS INTO 6, 9, OR 12 JOB FAMILIES  C
C           WHILE MAXIMIZING PREDICTIVE VALIDITY        C
C-----------------------------------------------------C
C
C * FUNCTIONS AND SUBROUTINES APPEAR FIRST IN THE PROGRAM
C
C * SUBROUTINE THAT INCREASES THE ROW DESIGNATORS AS NEEDED(CHOOSE 3)
C * CALL CHECK3(R1,R2,R3,X)
C * (FOR STAGE 1)
      SUBROUTINE CHECK3(X,Y,Z,MAX)
      INTEGER X, Y, Z, MAX
      IF (X .LE. (MAX-2)) THEN
         IF (Y .EQ. (MAX-1)) THEN
            X = X+1
            Y = X+1
            Z = Y+1
            END IF
         END IF
      IF (Z .GT. MAX) THEN
         Y = Y+1
         Z = Y+1
         END IF
      RETURN
      END
C * SUBROUTINE THAT INCREASES THE ROW DESIGNATORS AS NEEDED(CHOOSE 2)
C * CALL CHECK2(R1,R2,X)
C * (FOR STAGE 1)
      SUBROUTINE CHECK2(X,Y,MAX)
      INTEGER X, Y, MAX
      IF (X .LE. (MAX-1)) THEN
         IF (Y .GT. MAX) THEN
            X = X+1
            Y = X+1
            END IF
          END IF
      RETURN
      END
C * FUNCTION LOWR2 RETURNS ROW NUMBER WITH LOWEST R2 VALUE
C * ONLY CONSIDERS ROWS ELIGIBLE TO BE SELECTED
C * (FOR STAGE 2)
      INTEGER FUNCTION LOWR2(M,X,Y)
         INTEGER X, Y, TEMPRW
         REAL M, TEMPRL, LOW
         DIMENSION M(12,45)
         LOW = 800.00
         TEMPRW = 0
         DO 20 I = 1,X
            IF (M(I,(Y+2)) .EQ. 0.0) THEN
               TEMPRL = M(I,Y)
               IF (TEMPRL .LT. LOW) THEN
                  LOW = TEMPRL
                  TEMPRW = I
                  END IF
               END IF
20       CONTINUE
         LOWR2 = TEMPRW
         RETURN
         END
C * SUBROUTINE HIGHR2 RETURNS ROW NUMBER WITH THE HIGHEST R2 VALUE
C * CALL HIGHR2(M1,PROW1,RN,Y+1)
C * (FOR STAGE 2)
      SUBROUTINE HIGHR2(M,FINAL,X,Y)
         INTEGER X, Y, TEMPRW, I, FINAL
         REAL M, TEMPRL, HIGH
         DIMENSION M(12,45)
         HIGH = -1.00
         TEMPRW = 1
```

```
         DO 40 I = 1,X
            TEMPRL = M(I,Y)
               IF (TEMPRL .GT. HIGH) THEN
                  HIGH = TEMPRL
                  TEMPRW = I
               END IF
40       CONTINUE
         FINAL = TEMPRW
         WRITE (6,45) FINAL
45       FORMAT (/1X, 'HIGHEST R2:', I2)
         RETURN
         END
C * SUBROUTINE CALC2 CREATES TEMPORARY MATRICES M1 AND M2 WHEN THERE
C * ARE ONLY 2 JOBS IN THE ROW TO BE COMBINED WITH ALL OTHER ROWS
C * CALL CALC2(V,CJOB,ROW,HOWMNY,NUMCOL,Y,RN,M1,M2)
C * (FOR STAGE 2)
      SUBROUTINE CALC2(M,X,Y,I,J,K,L,A1,A2)
        INTEGER I, J, K, L, A, N, X, Y
        REAL M, A1, A2, TEMP1, TEMP2
        DIMENSION M(18,29), A1(12,45), A2(12,45), X(18), Y(18)
        DO 60 N = 1,K
           IF (N .LE. I) THEN
              A1(L,(N+K+3)) = Y(N)
              A2(L,(N+K+3)) = Y(N)
              END IF
           TEMP1 = 0
           TEMP2 = 0
           DO 55 A = 1,I
              TEMP1 = TEMP1 + M(Y(A),N)
              TEMP2 = TEMP2 + M(Y(A),N)
55         CONTINUE
           A1(L,N) = (TEMP1 + M(X(1),N))/(I+1)
           A2(L,N) = (TEMP2 + M(X(2),N))/(I+1)
60      CONTINUE
        A1(L,(N+1)) = I + 1
        A1(L,(N+2)) = 1
        A1(L,(N+A+2)) = X(1)
        A2(L,(N+1)) = I + 1
        A2(L,(N+2)) = 1
        A2(L,(N+A+2)) = X(2)
        RETURN
        END
C * SUBROUTINE CALC3 CREATES TEMPORARY MATRICES M1, M2, M3 WHEN THERE
C * ARE 3 JOBS IN THE ROW TO BE COMBINED WITH ALL OTHER ROWS
C * CALL CALC3(V,CJOB,ROW,HOWMNY,NUMCOL,Y,RN,M1,M2,M3)
C * (FOR STAGE 2)
      SUBROUTINE CALC3(M,X,Y,I,J,K,L,A1,A2,A3)
        INTEGER I, J, K, L, A, N, X, Y
        REAL M, A1, A2, A3, TEMP1, TEMP2, TEMP3
        DIMENSION M(18,29), A1(12,45), A2(12,45), A3(12,45)
        DIMENSION X(18), Y(18)
        DO 80 N = 1,K
           IF (N .LE. I) THEN
              A1(L,(N+K+3)) = Y(N)
              A2(L,(N+K+3)) = Y(N)
              A3(L,(N+K+3)) = Y(N)
              END IF
           TEMP1 = 0
           TEMP2 = 0
           TEMP3 = 0
           DO 75 A = 1,I
              TEMP1 = TEMP1 + M(Y(A),N)
              TEMP2 = TEMP2 + M(Y(A),N)
              TEMP3 = TEMP3 + M(Y(A),N)
75         CONTINUE
           A1(L,N) = (TEMP1 + M(X(1),N))/(I+1)
           A2(L,N) = (TEMP2 + M(X(2),N))/(I+1)
           A3(L,N) = (TEMP3 + M(X(3),N))/(I+1)
80      CONTINUE
        A1(L,(N+1)) = I + 1
        A1(L,(N+2)) = 1
        A1(L,(N+A+2)) = X(1)
        A2(L,(N+1)) = I + 1
```

```
      A2(L,(N+2)) = 1
      A2(L,(N+A+2)) = X(2)
      A3(L,(N+1)) = I + 1
      A3(L,(N+2)) = 1
      A3(L,(N+A+2)) = X(3)
      RETURN
      END
C * SUBROUTINE AVGWR2 CALCULATES THE AVERAGE WEIGHTED R2 VALUE
C * CALL AVGWR2(TEMP1,NEWVL1,Y+1,Y+2,NUMCLS)
    SUBROUTINE AVGWR2(M,VALUE,X1,Y1,Z)
      INTEGER X1, Y1, Z, I
      REAL M, TEMP, VALUE
      DIMENSION M(12,45)
      TEMP = 0
      DO 90 I = 1,Z
         TEMP = TEMP + (M(I,X1) * M(I,Y1))
90    CONTINUE
      VALUE = TEMP/18
      RETURN
      END
C * SUBROUTINE COPYMX COPIES AN ENTIRE MATRIX ONTO ANOTHER MATRIX
C * CALL COPYMX(NEWRES,TEMP1,Y,NUMCLS) OR
C * CALL COPYMX(TEMP1,NEWRES,Y,NUMCLS)
C * (FOR STAGE 2)
    SUBROUTINE COPYMX(A,B,C,D)
      INTEGER I, J, C, D
      REAL A, B
      DIMENSION A(12,45), B(12,45)
      DO 100 I = 1,D
         DO 99 J = 1,(C+16)
            B(I,J) = A(I,J)
99       CONTINUE
100   CONTINUE
      RETURN
      END
C * SUBROUTINE CREAT2 WILL CREATE 2 TEMPORARY MATRICES WITH THE ROW
C * HAVING THE HIGHEST R2 FROM M1 AND M2, RESPECTIVELY, SUBSTITUTED
C * INTO TEMP1 AND TEMP2-- IT WILL THEN BE POSSIBLE TO CALCULATE THE
C * AVERAGE WEIGHTED R2 TO DETERMINE IF ONE OF THESE SHOULD REPLACE
C * NEWRES
C * CALL CREAT2(V,RINV,M1,M2,PROW1,PROW2,CJOB,Y,NUMCOL,NUMCLS,Y+16,
C *            CROW,TEMP1, TEMP2)
C * (FOR STAGE 2)
    SUBROUTINE CREAT2(A,R,B1,B2,X1,X2,Y1,K,L,M,N,P,TP1,TP2)
      INTEGER I, J, K, L, M, N, P, X1, X2, Y1
      REAL A, R, B, C, TP1, TP2, SUM1, SUM2, Q1, Q2
      REAL HOLD1, HOLD2, RSQ1, RSQ2
      DIMENSION A(18,29), R(29,29), B1(12,45), B2(12,45), Y1(18)
      DIMENSION TP1(12,45), TP2(12,45), HOLD1(29), HOLD2(29)
      DO 140 I = 1,M
         IF (TP1(I,(K+4)) .EQ. B1(X1,(K+4))) THEN
            DO 120 J = 1,N
               TP1(I,J) = B1(X1,J)
120         CONTINUE
            END IF
         IF (TP2(I,(K+4)) .EQ. B2(X2,(K+4))) THEN
            DO 130 J = 1,N
               TP2(I,J) = B2(X2,J)
130         CONTINUE
            END IF
140   CONTINUE
C * FIX THE TEMPORARY MATRICES SO THAT THE CROW(CHOSEN ROW) WHICH HAS
C * ONLY ONE JOB LEFT HAS THE CORRECT V VECTOR, RECALCULATE R2, AND
C * SET COUNTER CORRECTLY
      DO 150 J = 1,K
         TP1(P,J) = (A(Y1(2),J))/(L-1)
         TP2(P,J) = (A(Y1(1),J))/(L-1)
150   CONTINUE
      DO 160 I = 1,K
         SUM1 = 0
         SUM2 = 0
         DO 155 J = 1,K
            Q1 = TP1(P,J) * R(J,I)
```

```
               SUM1 = SUM1 + Q1
               Q2 = TP2(P,J) * R(J,I)
               SUM2 = SUM2 + Q2
155         CONTINUE
            HOLD1(I) = SUM1
            HOLD2(I) = SUM2
160      CONTINUE
         RSQ1 = 0
         RSQ2 = 0
         DO 170 J = 1,K
            Q1 = HOLD1(J) * TP1(P,J)
            RSQ1 = RSQ1 + Q1
            Q2 = HOLD2(J) * TP2(P,J)
            RSQ2 = RSQ2 + Q2
170      CONTINUE
C * STORE R2 VALUE, COUNTER VALUE, AND JOB DESIGNATORS
         TP1(P,J) = RSQ1
         TP2(P,J) = RSQ2
         TP1(P,(J+1)) = L-1
         TP2(P,(J+1)) = L-1
         TP1(P,(J+3)) = Y1(2)
         TP1(P,(J+4)) = 0.0
         TP1(P,(J+5)) = 0.0
         TP2(P,(J+3)) = Y1(1)
         TP2(P,(J+4)) = 0.0
         TP2(P,(J+5)) = 0.0
         RETURN
         END
C * SUBROUTINE CREAT3 WILL CREATE 3 TEMPORARY MATRICES WITH THE ROW
C * HAVING THE HIGHEST R2 FROM M1, M2, M3, RESPECTIVELY, SUBSTITUTED
C * INTO TEMP1,TEMP2,TEMP3. IT WILL THEN BE POSSIBLE TO CALCULATE THE
C * AVERAGE WEIGHTED R2 TO DETERMINE IF ONE OF THESE SHOULD REPLACE
C * NEWRES
C * CALL CREAT3(V,RINV,M1,M2,M3,PROW1,PROW2,PROW3,CJOB,Y,NUMCOL,
C *             NUMCLS,Y+16,CROW,TEMP1,TEMP2,TEMP3)
C * (FOR STAGE 2)
      SUBROUTINE CREAT3(A,R,B1,B2,B3,X1,X2,X3,Y1,K,L,M,N,P,TP1,TP2,TP3)
         INTEGER I, J, K, L, M, N, P, X1, X2, X3, Y1
         REAL A, R, B, C, TP1, TP2, TP3, SUM1, SUM2, SUM3, Q1, Q2, Q3
         REAL HOLD1, HOLD2, HOLD3, RSQ1, RSQ2, RSQ3
         DIMENSION A(18,29), R(29,29), B1(12,45), B2(12,45), B3(12,45)
         DIMENSION Y1(18), TP1(12,45), TP2(12,45), TP3(12,45)
         DIMENSION HOLD1(29), HOLD2(29), HOLD3(29)
         DO 250 I = 1,M
            IF (TP1(I,(K+4)) .EQ. B1(X1,(K+4))) THEN
               DO 220 J = 1,N
                  TP1(I,J) = B1(X1,J)
220            CONTINUE
               END IF
            IF (TP2(I,(K+4)) .EQ. B2(X2,(K+4))) THEN
               DO 230 J = 1,N
                  TP2(I,J) = B2(X2,J)
230            CONTINUE
               END IF
            IF (TP3(I,(K+4)) .EQ. B3(X3,(K+4))) THEN
               DO 240 J = 1,N
                  TP3(I,J) = B3(X3,J)
240            CONTINUE
               END IF
250      CONTINUE
C * FIX THE TEMPORARY MATRICES SO THAT THE CROW(CHOSEN ROW) WHICH HAS
C * TWO JOBS LEFT HAS THE CORRECT V VECTOR, RECALCULATE R2, AND
C * SET COUNTER CORRECTLY
         DO 252 J = 1,K
            TP1(P,J) = (A(Y1(2),J) + A(Y1(3),J))/(L-1)
            TP2(P,J) = (A(Y1(1),J) + A(Y1(3),J))/(L-1)
            TP3(P,J) = (A(Y1(1),J) + A(Y1(2),J))/(L-1)
252      CONTINUE
         DO 260 I = 1,K
            SUM1 = 0
            SUM2 = 0
            SUM3 = 0
            DO 255 J = 1,K
```

```
            Q1 = TP1(P,J) * R(J,I)
            SUM1 = SUM1 + Q1
            Q2 = TP2(P,J) * R(J,I)
            SUM2 = SUM2 + Q2
            Q3 = TP3(P,J) * R(J,I)
            SUM3 = SUM3 + Q3
255       CONTINUE
          HOLD1(I) = SUM1
          HOLD2(I) = SUM2
          HOLD3(I) = SUM3
260     CONTINUE
        RSQ1 = 0
        RSQ2 = 0
        RSQ3 = 0
        DO 270 J = 1,K
          Q1 = HOLD1(J) * TP1(P,J)
          RSQ1 = RSQ1 + Q1
          Q2 = HOLD2(J) * TP2(P,J)
          RSQ2 = RSQ2 + Q2
          Q3 = HOLD3(J) * TP2(P,J)
          RSQ3 = RSQ3 + Q3
270     CONTINUE
C * STORE R2 VALUE, COUNTER VALUE, AND JOB DESIGNATORS
        TP1(P,J) = RSQ1
        TP2(P,J) = RSQ2
        TP3(P,J) = RSQ3
        TP1(P,(J+1)) = L-1
        TP2(P,(J+1)) = L-1
        TP3(P,(J+1)) = L-1
        TP1(P,(J+3)) = Y1(2)
        TP1(P,(J+4)) = Y1(3)
        TP1(P,(J+5)) = 0.0
        TP2(P,(J+3)) = Y1(1)
        TP2(P,(J+4)) = Y1(3)
        TP2(P,(J+5)) = 0.0
        TP3(P,(J+3)) = Y1(1)
        TP3(P,(J+4)) = Y1(2)
        TP3(P,(J+5)) = 0.0
        RETURN
        END
C-----------------------------------------------------------C
C MAIN PROGRAM (STAGE 1)                                    C
C      STAGE 1 WILL AVERAGE ALL POSSIBLE COMBINATIONS OF 3 OR  C
C      2 ROWS DEPENDING ON THE CONDITION, CALCULATE R2 FOR    C
C      EACH ROW, PICK LARGEST R2, AND END UP WITH EITHER      C
C      6, 9, OR 12 ROWS (ALL WITH DIFFERENT JOBS) WITH THE    C
C      HIGHEST R2.                                            C
C-----------------------------------------------------------C
C * DECLARE VARIABLES (BOTH STAGES)
      REAL RINV, V, RES, TRES, TOTRV, MULT, TOTAL, P1, P2, P3
      REAL NRES, NEWRES, M1, M2, M3, TOTRV1, TOTRV2, TOTRV3
      REAL TM1, TM2, TM3, TOTAL1, TOTAL2, TOTAL3, MULT1, MULT2, MULT3
      REAL TEMP1, TEMP2, TEMP3, ORGVAL, NEWVL1, NEWVL2, NEWVL3
      DIMENSION RINV(29,29), V(18,29), RES(816,33), TRES(29,816)
      DIMENSION TOTRV(816,29), NRES(12,33), NEWRES(12,45)
      DIMENSION M1(12,45), M2(12,45), M3(12,45)
      DIMENSION TEMP1(12,45), TEMP2(12,45), TEMP3(12,45)
      DIMENSION CJOB(18), ROW(18)
      DIMENSION TOTRV1(12,29), TOTRV2(12,29), TOTRV3(12,29)
      DIMENSION TM1(29,12), TM2(29,12), TM3(29,12)
      INTEGER NUMCLS, I, J, X, Y, R1, R2, R3, NC, VAL, P
      INTEGER LOCLRG, K, L, [illegible]OW, NUMCOL, HOWMNY, COUNT, RN, G
      INTEGER CJOB, ROW, PROW1, PROW2, PROW3
      CHARACTER*8 SOURCE
C * VARIABLES THAT WILL NEED TO BE CHANGED FOR EACH
C * DIFFERENT CONDITION
C * NUMBER OF CLUSTERS (06, 09, OR 12)
      NUMCLS = 12
C * DATA SOURCE (PROJA29, PROJA9, OR MCGL)
      SOURCE = 'PROJA29'
C * NUMBER OF ROWS IN VALIDITY MATRIX
      X = 18
C * NUMBER OF COLUMNS IN VALIDITY MATRIX
```

```
      Y = 29
C * CHOOSE VALUE (03 OR 02)
      VAL = 2
C * VALUE AFTER CALCULATION OF N CHOOSE M VALUE (816 OR 153)
      NC = 153
C * READ IN DATA FILES
      IF (SOURCE .EQ. 'PROJA29') THEN
          READ (5,36) ((RINV(I,J), J=1,29), I=1,29)
          READ (5,36) ((V(I,J), J=1,29), I=1,18)
36        FORMAT (29(1X,F9.6))
          END IF
      IF (SOURCE .EQ. 'PROJA9') THEN
          READ (5,40) ((RINV(I,J), J=1,9), I=1,9)
          READ (5,40) ((V(I,J), J=1,9), I=1,18)
40        FORMAT (8(1X,F9.6)/F9.6)
          END IF
      IF (SOURCE .EQ. 'MCGL') THEN
          READ (5,40) ((RINV(I,J), J=1,9), I=1,9)
          READ (5,40) ((V(I,J), J=1,9), I=1,18)
C          WRITE (6,50) ((RINV(I,J), J=1,9), I=1,9)
C          WRITE (6,50) ((V(I,J), J=1,9), I=1,18)
C 50        FORMAT (9(1X,F9.6))
          END IF
C * ZERO OUT RESULTS MATRICES
      DO 120 I = 1,NC
         DO 119 J = 1,(Y+4)
             RES(I,J) = 0
             TOTRV(I,J) = 0
             TRES(J,I) = 0
119      CONTINUE
120   CONTINUE
      IF (VAL .EQ. 3) GO TO 130
      IF (VAL .EQ. 2) GO TO 150
C * CALCULATE THE RESULTS MATRIX FOR CHOOSE 3 VALUE
C * ROW DESIGNATORS PLACED IN THE LAST THREE COLUMNS OF RESULTS MATRIX
130   R1 = 1
      R2 = R1 + 1
      R3 = R2 + 1
      DO 140 I = 1,NC
         CALL CHECK3(R1,R2,R3,X)
         DO 135 J = 1,Y
             RES(I,J) = (V(R1,J) + V(R2,J) + V(R3,J))/3.0
135      CONTINUE
             RES(I,J) = R1
             RES(I,J+1) = R2
             RES(I,J+2) = R3
             R3 = R3 + 1
140   CONTINUE
C * PRODUCE THE OUTPUT TO CHECK PROGRAM
C       WRITE (6,145) ((RES(I,J), J=1,(Y+VAL)), I=1,NC)
C 145   FORMAT (12(1X,F6.3))
      GO TO 175
C * CALCULATE THE RESULTS MATRIX FOR CHOOSE 2 VALUE
C * ROW DESIGNATORS PLACED IN THE LAST TWO COLUMNS OF RESULTS MATRIX
150   R1 = 1
      R2 = R1 + 1
      DO 170 I = 1,NC
         CALL CHECK2(R1,R2,X)
         DO 155 J = 1,Y
             RES(I,J) = (V(R1,J) + V(R2,J))/2.0
155      CONTINUE
             RES(I,J) = R1
             RES(I,J+1) = R2
             R2 = R2 + 1
170   CONTINUE
C * PRODUCE THE OUTPUT TO CHECK PROGRAM
C       WRITE (6,172) ((RES(I,J), J=1,(Y+VAL)), I=1,NC)
C 172   FORMAT (11(1X,F6.3))
C
C * FOR THE 12 JOB CLUSTERS CONDITION THE ORIGINAL 18 BY Y VALIDITY
C * MATRIX MUST BE ADDED TO THE BOTTOM OF THE RESULTS MATRIX
175   IF (NUMCLS .EQ. 12) THEN
          P = 1
```

```
          DO 190 I = (NC+1), (NC+X)
             DO 185 J = 1,Y
                RES(I,J) = V(P,J)
185          CONTINUE
             RES(I,J) = P
             RES(I,J+1) = P
             P = P+1
190       CONTINUE
          NC = NC + 18
          END IF
C
C * TRANSPOSE RESULTS MATRIX (I.E., TRANSPOSE AVERAGE VALIDITY MATRIX)
       DO 200 I = 1,NC
          DO 199 J = 1,Y
             TRES(J,I) = RES(I,J)
199       CONTINUE
200    CONTINUE
C
C * THE NEXT SECTION CALCULATES V * R(INVERSE) * V(TRANSPOSED)
C * AND OUTPUT R2 AS ANOTHER COLUMN IN THE RESULTS MATRIX
       DO 220 I = 1,NC
          DO 219 P = 1,Y
             TOTAL = 0
             DO 217 J = 1,Y
                MULT = RES(I,J) * RINV(J,P)
                TOTAL = TOTAL + MULT
217          CONTINUE
             TOTRV(I,P) = TOTAL
219       CONTINUE
220    CONTINUE
       DO 230 I = 1,NC
          TOTAL = 0
          DO 228 J = 1,Y
             MULT = TOTRV(I,J) * TRES(J,I)
             TOTAL = TOTAL + MULT
228       CONTINUE
          RES(I,(Y+VAL+1)) = TOTAL
230    CONTINUE
C * PRODUCE THE OUTPUT TO CHECK PROGRAM
C      WRITE (6,235) ((RES(I,J), J=1,(Y+VAL+1)), I=1,NC)
C 235   FORMAT (33(1X,F6.3))
C
C * THE NEXT SECTION WILL LOCATE THE LARGEST R2S, AND STORE THE DATA
C * IN THESE ROWS CORRESPONDING TO THE LARGEST R2
C * ALL OTHER R2 VALUES ARE SET TO ZERO WHENEVER THE SAME JOB #'S
C * HAVE ALREADY BEEN SELECTED
       DO 400 K = 1, NUMCLS
          LOCLRG = 1
          J = Y + VAL + 1
C * FOR 12 CONDITION MUST DO SOMETHING DIFFERENT WHEN K > 6
          IF (NUMCLS .EQ. 12) THEN
             IF (K .GT. 6) GO TO 405
             NC = NC-18
             END IF
C * LOCATE LARGEST R2 VALUE
          DO 260 I = 2,NC
             IF (RES(I,J) .GT. RES(LOCLRG,J)) THEN
                 LOCLRG = I
                 END IF
260       CONTINUE
C * CREATE TEMPORARY HRES MATRIX TO STORE THE EVOLVING CLUSTERS
          DO 270 L = 1,J
             HRES(K,L) = RES(LOCLRG,L)
270       CONTINUE
C * SET R2 VALUES TO ZERO THAT HAVE THE SAME JOB DESIGNATORS
          IF (VAL .EQ. 3) GO TO 300
          IF (VAL .EQ. 2) GO TO 350
300       P1 = RES(LOCLRG,(J-3))
          P2 = RES(LOCLRG,(J-2))
          P3 = RES(LOCLRG,(J-1))
          DO 330 I = 1,NC
             IF ((P1 .EQ. RES(I,(J-3))) .OR. (P1 .EQ. RES(I,(J-2))) .OR.
     +          (P1 .EQ. RES(I,(J-1)))) THEN
```

```
                  RES(I,J) = 0
                  END IF
               IF ((P2 .EQ. RES(I,(J-3))) .OR. (P2 .EQ. RES(I,(J-2))) .OR.
     +            (P2 .EQ. RES(I,(J-1)))) THEN
                  RES(I,J) = 0
                  END IF
               IF ((P3 .EQ. RES(I,(J-3))) .OR. (P3 .EQ. RES(I,(J-2))) .OR.
     +            (P3 .EQ. RES(I,(J-1)))) THEN
                  RES(I,J) = 0
                  END IF
330         CONTINUE
            GO TO 400
350         P1 = RES(LOCLRG,(J-2))
            P2 = RES(LOCLRG,(J-1))
356         IF (NUMCLS .EQ. 12) THEN
               NC = NC+18
               END IF
            DO 380 I = 1,NC
               IF ((P1 .EQ. RES(I,(J-2))) .OR. (P1 .EQ. RES(I,(J-1)))) THEN
                  RES(I,J) = 0
                  END IF
               IF ((P2 .EQ. RES(I,(J-2))) .OR. (P2 .EQ. RES(I,(J-1)))) THEN
                  RES(I,J) = 0
                  END IF
380         CONTINUE
400      CONTINUE
C * FOR THE 12 CLUSTER CONDITION THE HIGHEST R2 FOR 6 SINGLE JOBS
C * MUST BE IDENTIFIED AND ORDERED
405      IF (NUMCLS .EQ. 12) THEN
         DO 420 K = 7,12
            LOCLRG = NC-17
            J = Y+VAL+1
            DO 410 I = (NC-16),NC
               IF (RES(I,J) .GT. RES(LOCLRG,J)) THEN
                  LOCLRG = I
                  END IF
410         CONTINUE
C * FOR THE 12 CLUSTER CONDITION FINISH THE LAST 6 ROWS OF HRES
C * AND SET R2 VALUE TO ZERO FOR THAT ROW
            DO 415 L = 1,J
               HRES(K,L) = RES(LOCLRG,L)
415         CONTINUE
            RES(LOCLRG,J) = 0
420      CONTINUE
         ENDIF
C * WRITE OUT INITIAL CLUSTERS (STORED IN HRES)
C        WRITE (6,422)
C 422      FORMAT (/1X, 'INITIAL CLUSTERS')
C          IF (VAL .EQ. 3) THEN
C             IF (SOURCE .EQ. 'PROJA29') THEN
C                WRITE (6,424) ((HRES(I,J), J=1,33), I=1,NUMCLS)
C 424              FORMAT (33(1X,F5.2))
C                GO TO 440
C                END IF
C             WRITE (6,426) ((HRES(I,J), J=1,13), I=1,NUMCLS)
C 426           FORMAT (13(1X,F6.3))
C             END IF
C        IF (VAL .EQ. 2) THEN
C           IF (SOURCE .EQ. 'PROJA29') THEN
C              WRITE (6,428) ((HRES(I,J), J=1,32), I=1,NUMCLS)
C 428              FORMAT (32(1X,F5.2))
C                GO TO 440
C              END IF
C           WRITE (6,430) ((HRES(I,J), J=1,12), I=1,NUMCLS)
C 430         FORMAT (12(1X,F6.3))
C             END IF
C------------------------------------------------------------------C
C STAGE 2                                                          C
C     STAGE 2 WILL SHRED OUT THE INITIAL SET OF CLUSTERS TO        C
C     DETERMINE IF THERE IS A MORE OPTIMAL COMBINATION OF JOBS     C
C     THAN THE INITIAL CORE CLUSTERS.                              C
C------------------------------------------------------------------C
C
```

```
C * CREATE MATRIX NEWRES THAT IS THE SAME AS THE HRES MATRIX
C * BUT WITH THE COLUMNS AT END OF MATRIX IN DIFFERENT PLACES.
C * THIS GIVE UNLIMITED SPACE TO STORE THE JOB DESIGNATORS.
C * R2 VALUE STORED IN COLUMN 10 (OR 30)
C * A COUNTER VALUE STORED IN COLUMN 11 (OR 31)
C * A "SELECTED" DESIGNATOR STORED IN COLUMN 12 (OR 32)
C * JOB DESIGNATORS ARE STORED IN COLUMNS 13 (OR 33) ON.
C * STORE DATA VALUES FIRST
440   DO 450 I = 1,NUMCLS
         DO 449 J = 1,Y
            NEWRES(I,J) = HRES(I,J)
449      CONTINUE
450   CONTINUE
C * STORE R2 AND INITIALIZE "SELECTED" VALUE TO ZERO
      DO 455 I = 1,NUMCLS
         NEWRES(I,(Y+1)) = HRES(I,(Y+VAL+1))
         NEWRES(I,(Y+3)) = 0
455   CONTINUE
C * STORE JOB DESIGNATORS AND CREATE COUNTER
         IF (VAL .EQ. 3) THEN
            DO 460 I = 1,NUMCLS
               NEWRES(I,(Y+4)) = HRES(I,(Y+1))
               NEWRES(I,(Y+5)) = HRES(I,(Y+2))
               NEWRES(I,(Y+6)) = HRES(I,(Y+3))
               NEWRES(I,(Y+2)) = 3.0
460         CONTINUE
            END IF
         IF (VAL .EQ. 2) THEN
            DO 470 I = 1,NUMCLS
               NEWRES(I,(Y+4)) = HRES(I,(Y+1))
               NEWRES(I,(Y+5)) = HRES(I,(Y+2))
               NEWRES(I,(Y+2)) = 2.0
470         CONTINUE
            END IF
         IF (NUMCLS .EQ. 12) THEN
            DO 475 I = 7,12
               NEWRES(I,(Y+2)) = 1.0
               NEWRES(I,(Y+3)) = 1.0
475         CONTINUE
            END IF
      WRITE (6,483)
483   FORMAT (/1X, 'NEWRES MATRIX')
      WRITE (6,485) ((NEWRES(I,J), J=(Y+1),(Y+VAL+3)), I=1,NUMCLS)
485   FORMAT (5(1X,F6.3))
C
C * CALCULATE THE INITIAL AVERAGE WEIGHTED R2 VALUE FOR NEWRES
      CALL AVGWR2(NEWRES,ORGVAL,Y+1,Y+2,NUMCLS)
      WRITE (6,490) ORGVAL
490   FORMAT(/1X, 'INITIAL R2 VALUE FOR NEWRES:',1X,F8.6)
C
C * INITIALIZE THE ITERATION COUNTER
      G = 0
C
C * INITIALIZE M1, M2, M3, TEMP1, TEMP2, TEMP3
500   DO 505 I = 1,NUMCLS
         DO 504 J = 1,(Y+16)
            M1(I,J) = 0
            M2(I,J) = 0
            M3(I,J) = 0
            TEMP1(I,J) = 0
            TEMP2(I,J) = 0
            TEMP3(I,J) = 0
504      CONTINUE
505   CONTINUE
C * INITIALIZE TOTRV1, TOTRV2, TOTRV3 TO BE USED IN CALC OF R2
      DO 510 I = 1,NUMCLS
         DO 509 J = 1,Y
            TOTRV1(I,J) = 0
            TOTRV2(I,J) = 0
            TOTRV3(I,J) = 0
509      CONTINUE
510   CONTINUE
C
```

```
C * CHOOSE THE ROW FROM NEWRES TO BE COMBINED (ONE JOB AT A TIME)
C * WITH THE OTHER ROWS
      CROW = LOWR2(NEWRES,NUMCLS,(Y+1))
C
C * THE NEXT STATEMENT PROVIDES THE LOOP TO END THE PROGRAM IF ALL
C * ROWS THAT ARE ELIGIBLE TO BE SELECTED HAVE BEEN SELECTED
      IF (CROW .GT. 0) THEN
      G = G + 1
C
C * SET THE "SELECTED" VALUE TO 1 FOR THE CROW JUST CHOSEN
      NEWRES(CROW,(Y+3)) = 1.0
C * OBTAIN THE COUNTER VALUE FOR THIS ROW
      NUMCOL = INT(NEWRES(CROW,(Y+2)))
C * OBTAIN THE JOB DESIGNATORS FOR THIS ROW
      DO 530 I=1,NUMCOL
         CJOB(I) = INT(NEWRES(CROW,(Y+3+I)))
530   CONTINUE
C
C * CREATE THE TEMPORARY MATRICES (M1,M2,M3)
      RN = 0
      DO 550 I = 1,NUMCLS
         IF (I .NE. CROW) THEN
            RN = RN + 1
            HOWMNY = INT(NEWRES(I,(Y+2)))
            DO 540 K = 1,HOWMNY
               ROW(K) = INT(NEWRES(I,(Y+3+K)))
540         CONTINUE
            IF (NUMCOL .EQ. 2) THEN
               CALL CALC2(V,CJOB,ROW,HOWMNY,NUMCOL,Y,RN,M1,M2)
               END IF
            IF (NUMCOL .EQ. 3) THEN
               CALL CALC3(V,CJOB,ROW,HOWMNY,NUMCOL,Y,RN,M1,M2,M3)
               END IF
            END IF
550   CONTINUE
C
C * TRANSPOSE M1, M2, AND M3 TO BE USED IN THE CALC OF R2
       DO 570 I = 1,(NUMCLS-1)
          DO 569 J = 1,Y
             TM1(J,I) = M1(I,J)
             TM2(J,I) = M2(I,J)
             IF (NUMCOL .EQ. 2) GO TO 569
             TM3(J,I) = M3(I,J)
569       CONTINUE
570    CONTINUE
C * CALCULATE R2 VALUE FOR M1, M2, M3 (ONLY CALCULATES R2 FOR M3 IF
C * NUMCOL EQUALS 3)
      DO 650 I = 1,(NUMCLS-1)
         DO 645 P = 1,Y
            TOTAL1 = 0
            TOTAL2 = 0
            TOTAL3 = 0
            DO 600 J = 1,Y
               MULT1 = M1(I,J) * RINV(J,P)
               TOTAL1 = TOTAL1 + MULT1
600         CONTINUE
            TOTRV1(I,P) = TOTAL1
            DO 620 J = 1,Y
               MULT2 = M2(I,J) * RINV(J,P)
               TOTAL2 = TOTAL2 + MULT2
620         CONTINUE
            TOTRV2(I,P) = TOTAL2
            IF (NUMCOL .EQ. 2) GO TO 645
            DO 630 J = 1,Y
               MULT3 = M3(I,J) * RINV(J,P)
               TOTAL3 = TOTAL3 + MULT3
630         CONTINUE
            TOTRV3(I,P) = TOTAL3
645      CONTINUE
650   CONTINUE
      DO 730 I = 1,(NUMCLS-1)
         TOTAL1 = 0
         TOTAL2 = 0
```

```
      TOTAL3 = 0
      DO 710 J = 1,Y
         MULT1 = TOTRV1(I,J) * TM1(J,I)
         TOTAL1 = TOTAL1 + MULT1
         MULT2 = TOTRV2(I,J) * TM2(J,I)
         TOTAL2 = TOTAL2 + MULT2
         IF (NUMCOL .EQ. 2) GO TO 710
         MULT3 = TOTRV3(I,J) * TM3(J,I)
         TOTAL3 = TOTAL3 + MULT3
710   CONTINUE
      M1(I,(Y+1)) = TOTAL1
      M2(I,(Y+1)) = TOTAL2
      IF (NUMCOL .EQ. 2) GO TO 730
      M3(I,(Y+1)) = TOTAL3
730   CONTINUE
      WRITE (6,735) G
735   FORMAT (/1X, 'ITERATION NUMBER:', 1X, I2)
C * WRITE OUT COUNTERS AND JOB NUMBERS FOR M1, M2, AND M3
C * TO CHECK THE PROGRAM
      WRITE (6,770)
770   FORMAT (/1X, 'M1')
      WRITE (6,772) ((M1(I,J), J=(Y+1),(Y+16)), I=1,(NUMCLS-1))
772   FORMAT (16(1X,F6.3))
      WRITE (6,774)
774   FORMAT (/1X, 'M2')
      WRITE (6,772) ((M2(I,J), J=(Y+1),(Y+16)), I=1,(NUMCLS-1))
      IF (NUMCOL .EQ. 2) GO TO 800
      WRITE (6,776)
776   FORMAT (/1X, 'M3')
      WRITE (6,772) ((M3(I,J), J=(Y+1),(Y+16)), I=1,(NUMCLS-1))
C
C * THE NEXT SECTION PULLS OUT THE HIGHEST R2 FROM M1, M2, M3,
C * SUBSTITUTES THE APPROPRIATE ROWS TO CREATE A NEW "TEMP"
C * MATRIX, CALCULATES THE AVERAGE WEIGHTED R2 FOR EACH TEMP MATRIX AND
C * PICKS THE HIGHEST WEIGHTED AVERAGE COMBINATION AS THE NEW "NEWRES"
800   IF (NUMCOL .EQ. 2) THEN
         CALL HIGHR2(M1,PROW1,RN,Y+1)
         CALL HIGHR2(M2,PROW2,RN,Y+1)
         CALL COPYMX(NEWRES,TEMP1,Y,NUMCLS)
         CALL COPYMX(NEWRES,TEMP2,Y,NUMCLS)
         CALL CREAT2(V,RINV,M1,M2,PROW1,PROW2,CJOB,Y,NUMCOL,NUMCLS,
     +        Y+16,CROW,TEMP1,TEMP2)
         CALL AVGWR2(TEMP1,NEWVL1,Y+1,Y+2,NUMCLS)
         CALL AVGWR2(TEMP2,NEWVL2,Y+1,Y+2,NUMCLS)
C * WRITE OUT TEMP MATRICES AND WEIGHTED R2 VALUES TO CHECK PROGRAM
         WRITE (6,820)
820      FORMAT (/1X, 'TEMPORARY MATRIX 1')
         WRITE (6,822) ((TEMP1(I,J), J=(Y+1),(Y+16)), I=1,NUMCLS)
822      FORMAT (16(1X,F6.3))
         WRITE (6,824)
824      FORMAT (/1X, 'TEMPORARY MATRIX 2')
         WRITE (6,822) ((TEMP2(I,J), J=(Y+1),(Y+16)), I=1,NUMCLS)
         WRITE (6,826) .'EWVL1
826      FORMAT (/1X, 'TEMP1 WEIGHTED R2:', 1X, F8.6)
         WRITE (6,828) NEWVL2
828      FORMAT (/1X, 'TEMP2 WEIGHTED R2:', 1X, F8.6)
C * COMPARE WEIGHTED R2 VALUES WITH ORIGINAL WEIGHTED R2
C * MATRIX WITH THE HIGHEST WEIGHTED R2 BECOMES THE NEW "NEWRES"
         IF (NEWVL1 .GT. ORGVAL) THEN
            CALL COPYMX(TEMP1,NEWRES,Y,NUMCLS)
            ORGVAL = NEWVL1
            END IF
         IF (NEWVL2 .GT. ORGVAL) THEN
            CALL COPYMX(TEMP2,NEWRES,Y,NUMCLS)
            ORGVAL = NEWVL2
            END IF
         WRITE (6,850)
850      FORMAT (/1X, 'THE NEW SET OF JOB CLUSTERS')
         WRITE (6,852) ((NEWRES(I,J), J=(Y+1),(Y+16)), I=1,NUMCLS)
852      FORMAT (16(1X,F6.3))
         WRITE (6,854) ORGVAL
854      FORMAT (/1X, 'WEIGHTED R2 EQUALS:', 1X, F8.6)
         GO TO 500
```

```
          END IF
       IF (NUMCOL .EQ. 3) THEN
          CALL HIGHR2(M1,PROW1,RN,Y+1)
          CALL HIGHR2(M2,PROW2,RN,Y+1)
          CALL HIGHR2(M3,PROW3,RN,Y+1)
          CALL COPYMX(NEWRES,TEMP1,Y,NUMCLS)
          CALL COPYMX(NEWRES,TEMP2,Y,NUMCLS)
          CALL COPYMX(NEWRES,TEMP3,Y,NUMCLS)
          CALL CREAT3(V,RINV,M1,M2,M3,PROW1,PROW2,PROW3,CJOB,Y,
     +        NUMCOL,NUMCLS,Y+16,CROW,TEMP1,TEMP2,TEMP3)
          CALL AVGWR2(TEMP1,NEWVL1,Y+1,Y+2,NUMCLS)
          CALL AVGWR2(TEMP2,NEWVL2,Y+1,Y+2,NUMCLS)
          CALL AVGWR2(TEMP3,NEWVL3,Y+1,Y+2,NUMCLS)
C * WRITE OUT TEMP MATRICES AND WEIGHTED R2 VALUES TO CHECK PROGRAM
          WRITE (6,880)
880       FORMAT (/1X, 'TEMPORARY MATRIX 1')
          WRITE (6,882) ((TEMP1(I,J), J=(Y+1),(Y+16)), I=1,NUMCLS)
882       FORMAT (16(1X,F6.3))
          WRITE (6,884)
884       FORMAT (/1X, 'TEMPORARY MATRIX 2')
          WRITE (6,882) ((TEMP2(I,J), J=(Y+1),(Y+16)), I=1,NUMCLS)
          WRITE (6,886)
886       FORMAT (/1X, 'TEMPORARY MATRIX 3')
          WRITE (6,882) ((TEMP3(I,J), J=(Y+1),(Y+16)), I=1,NUMCLS)
          WRITE (6,888) NEWVL1
888       FORMAT (/1X, 'TEMP1 WEIGHTED R2:', 1X, F8.6)
          WRITE (6,890) NEWVL2
890       FORMAT (/1X, 'TEMP2 WEIGHTED R2:', 1X, F8.6)
          WRITE (6,900) NEWVL3
900       FORMAT (/1X, 'TEMP3 WEIGHTED R2:', 1X, F8.6)
C * COMPARE WEIGHTED R2 VALUES WITH ORIGINAL WEIGHTED R2.
C * MATRIX WITH THE HIGHEST WEIGHTED R2 BECOMES THE NEW "NEWRES".
          WRITE (6,910) ORGVAL
910       FORMAT (/1X, 'ORGVAL ', F8.6)
          IF (NEWVL1 .GT. ORGVAL) THEN
             CALL COPYMX(TEMP1,NEWRES,Y,NUMCLS)
             NEWRES(CROW,(Y+3)) = 0.0
             ORGVAL = NEWVL1
             END IF
          IF (NEWVL2 .GT. ORGVAL) THEN
             CALL COPYMX(TEMP2,NEWRES,Y,NUMCLS)
             NEWRES(CROW,(Y+3)) = 0.0
             ORGVAL = NEWVL2
             END IF
          IF (NEWVL3 .GT. ORGVAL) THEN
             CALL COPYMX(TEMP3,NEWRES,Y,NUMCLS)
             NEWRES(CROW,(Y+3)) = 0.0
             ORGVAL = NEWVL3
             END IF
          WRITE (6,950)
950       FORMAT (/1X, 'THE NEW SET OF JOB CLUSTERS')
          WRITE (6,952) ((NEWRES(I,J), J=(Y+1),(Y+16)), I=1,NUMCLS)
952       FORMAT (16(1X,F6.3))
          WRITE (6,954) ORGVAL
954       FORMAT (/1X, 'WEIGHTED R2 EQUALS:', 1X, F8.6)
          GO TO 500
          END IF
       END IF
       STOP
       END
```

APPENDIX I: PSEUDO-RANDOM NUMBER GENERATOR

1. FORTRAN SOURCE CODE (Davis Johnson, October, 1989)[1]

```
      PROGRAM GENX2
$INCLUDE: 'RANDOM.INC'
      INTEGER I,J,P
C     * DECLARE NORMAL 'RANDOM' FUNCTION
      REAL NORMAL
      EXTERNAL NORMAL
C     * DECLARE FLOOR (LARGEST INTEGER LESS THAN) FUNCTION
      INTEGER FLOOR
      EXTERNAL FLOOR
      REAL X,Y
      REAL SUM(1:6)
      INTEGER SAMPLE(-100:100),OUT,IN
      DATA SAMPLE/201*0/

C     * INITIALIZE RANDOM NUMBER GENERATOR INTERNAL DATA STRUCTURES
      CALL RANDINIT

C     *CREATE OUTPUT FILE
      OPEN(7,FILE='XX.DAT')

C     * GENERATE X MATRIX OF 17 BY NN
      CALL GENX
      STOP
      END

      REAL FUNCTION NORMAL()
C-----------------------------------------+
C
C FUNCTION:  NORMAL
C PURPOSE:   GENERATE A NORMALY GENERATED RANDOM NUMBER BY SUMMING
C            UNIFORMLY DISTRIBUTED NUMBERS.
C CALLING SYNTAX:
C            REAL NORMAL
C            EXTERNAL NORMAL
C            X=NORMAL()
C       where:
C            X RECEIVES A "NORMALLY"SELECTED VALUE
C
C-----------------------------------------+
$INCLUDE: 'RANDOM.INC'
      INTEGER I
      REAL RANDOM
      EXTERNAL RANDOM
      REAL NORMALIZE(0:39)
      DATA NORMALIZE/-2.3182, -1.8123, -1.5509, -1.3676, -1.2222,
     +         -1.0988, -0.9904, -0.8924, -0.8020, -0.7177,
     +         -0.6883, -0.5627, -0.4901, -0.4202, -0.4523,
     +         -0.2860, -0.2196, -0.1568, -0.0934, -0.0304,
     +         +0.0304, +0.0934, +0.1568, +0.2196, +0.2860,
     +         +0.4523, +0.4202, +0.4901, +0.5627, +0.6883,
     +         +0.7177, +0.8020, +0.8924, +0.9904, +1.0988,
     +         +1.2222, +1.3676, +1.5509, +1.8123, +2.3182/


      NORMAL=0.0
      IF(TFLAG.EQ.1)THEN
        DO 1 I=1,NUNIFORM
          NORMAL=NORMAL+RANDOM()
1     CONTINUE
      ELSE
```

[1] Algorithm from Park and Miller (1988); multipliers from Fishman and Moore (1986).

```
      DO 2 I=1,NUNIFORM
        NORMAL=NORMAL+NORMALIZE(INT(RANDOM()/0.025))
  2   CONTINUE
    END IF
    NORMAL=(NORMAL-OFFSET)*SCALE
    RETURN
    END

    REAL FUNCTION RANDOM
C--------------------------------------------+
C
C FUNCTION:   RANDOM
C PURPOSE:    GENERATE A UNIFORMLY DISTRIBUTED RANDOM NUMBER USING THE
C             ALGORITHIM PROPOSED IN "RANDOM NUMBER GENERATORS: GOOD
C             ONES ARE HARD TO FIND" CACM, 10/88
C CALLING SYNTAX:
C             REAL RANDOM
C             EXTERNAL RANDOM
C             X=RANDOM()
C      where:
C             X RECEIVES A "RANDOMLY"SELECTED, WHERE 0.0<=X<1.0
C
C--------------------------------------------+
$INCLUDE: 'RANDOM.INC'
    REAL*8 MODULUS
    PARAMETER (MODULUS=2 147 483 647.0D0)

    SEED(S,M)=DMOD(SEED(S,M)*MULT(M),MODULUS)
    RANDOM=SEED(S,M)/MODULUS

C    * SELECT NEXT MULTIPLIER
    M=MOD(M+1,NMULTS)
C    * SELECT NEXT SEED SEQUENCE
    IF(M.EQ.0) S=MOD(S+1,NSEEDS)
    RETURN
    END

    SUBROUTINE RANDINIT
C--------------------------------------------+
C
C SUBROUTINE: RANDINIT
C PURPOSE:    INITIAIZE DATA STRUCTURES REQUIRED BY THE RANDOM NUMBER
C             GENERATION ROUTINES.
C SYNTAX:     CALL RANDINIT
C
C--------------------------------------------+
    REAL*8 MODULUS
    PARAMETER (MODULUS=2 147 483 647.0D0)
    INTEGER I,J
    REAL*8 LSEED
$INCLUDE: 'RANDOM.INC'
C    * PROGRAMMINGNOTE: THIS IS AN EXAMPLE OF HOW TO DO A 'WHILE' LOOP,
C    * IN THIS CASE, 'WHILE NMULTS=0 DO...'
    NMULTS=0
  1 IF(NMULTS.LT.1 .OR. NMULTS.GT.MAXMULTS)THEN
      WRITE(6,'(" USING A DIFFERENT MULTIPLIER RESULTS IN")')
        WRITE(6,'(" A DIFFERENT RANDOM NUMBER SEQUENCE.")')
      WRITE(6,
   +    '(" ENTER NUMBER OF DIFFERENT MULTIPLIERS TO USE: "$)')
      READ(5,'(I3)')NMULTS
      GOTO 1
    END IF
    NUNIFORM=0
  2 IF(NUNIFORM.LT.1 .OR. NUNIFORM.GT.200)THEN
      WRITE(6,'(" NORMAL DEVIATES ARE PRODUCED BY SUMMING A")')
      WRITE(6,
   +    '(" NUMBER OF UNIFORM DEVIATES.  THIS NUMBER MAY BE")')
      WRITE(6,'(" THE SAME AS THE NUMBER OF MULTIPLIERS")')
      WRITE(6,'(" ENTER NUMBER OF UNIFORM DEVIATES TO USE: "$)')
      READ(5,'(I3)')NUNIFORM
      GOTO 2
    END IF
    NSEEDS=0
```

```
   3 IF(NSEEDS.LT.1 .OR. NSEEDS .GT. MAXSEEDS)THEN
       WRITE(6,'(" USING A DIFFERENT SEED RESULTS IN THE RANDOM")')
       WRITE(6,'(" SEQUENCE STARTING AT A DIFFERENT POINT.")')
       WRITE(6,'(" ENTER THE NUMBER OF SEEDS PER MULTIPLIER: "$)')
       READ(5,'(I3)')NSEEDS
       GOTO 3
     END IF
     TFLAG=0
   4 IF(TFLAG.LT.1 .OR. TFLAG.GT.2)THEN
       WRITE(6,
     +     '(" THE UNIFORMLY DEVIATES MAY BE TRANSFORMED INTO")')
       WRITE(6,
     +     '(" NORMAL DEVIATES BY A TABLE LOOKUP PROCESS BEFORE")')
       WRITE(6,'(" SUMMING.")')
       WRITE(6,
     +     '(" ENTER 1 TO DISABLE TRANSFORMATION,2 TO ENABLE: "$)')
       READ(5,*)TFLAG
       GOTO 4
     END IF
     IF(TFLAG.EQ.2)THEN
       OFFSET=0
       SCALE=SQRT(NUNIFORM)/NUNIFORM
     ELSE
       OFFSET=NUNIFORM/2.0
       SCALE=SQRT(12.0/NUNIFORM)
     END IF
C    * INITIALIZE SEED ARRAY USING A 'PRIVATE' GENERATOR
     LSEED=0
   5 IF(LSEED.EQ.0)THEN
       WRITE(6,'(" ENTER THE INITIALIZATIONSEED: "$)')
       READ(5,*)LSEED
       GOTO 5
     END IF
     DO 7 I=0,NSEEDS-1
       DO 6 J=0,NMULTS-1
         LSEED=DMOD(LSEED*1704318220D0,MODULUS)
         SEED(I,J)=LSEED
   6   CONTINUE
       WRITE(6,'(" ",10F12.0)')(SEED(I,J),J=0,NMULTS-1)
   7 CONTINUE
     WRITE(6,'(" NEXT INITIALIZATIONSEED: ",F12.0)')LSEED
     RETURN
     END
     INTEGER FUNCTION FLOOR(X)
     REAL X
     IF(X.LT.0.0)THEN
       FLOOR=INT(X)-1
     ELSE
       FLOOR=INT(X)
     END IF
     RETURN
     END

C    * SUBROUTINE TO GENERATE X MATRIX OF RND'S
     SUBROUTINE GENX
     INTEGER I,J,NN
     REAL XSAMPLE(30,600)
     REAL NORMAL
     EXTERNAL NORMAL
$INCLUDE: 'RANDOM.INC'
     WRITE(6,'(" ENTER SAMPLE SIZE: "$)')
     READ(5,*)NN
     DO 2 I=1,NMULTS
      DO 1 J=1,NN
        XSAMPLE(I,J)=NORMAL()
   1  CONTINUE
   2 CONTINUE
C    WRITE(7,*)NN
     WRITE(7,*) ((XSAMPLE(I,J),J=1,NN),I=1,20)
     RETURN
     END

     BLOCK DATA
```

```
$INCLUDE: 'RANDOM.INC'
      DATA MULT/1493834601D0,1037566960D0, 743722486D0,1509089937D0,
     +         1567699476D0,1947306937D0,1076532097D0,1957811727D0,
     +          628467148D0,1040895393D0, 786824435D0, 556530824D0,
     +          87921290D0, 1457913431D0, 385787459D0,1567316532D0,
     +          930959341D0,1588813465D0,1035519219D0,  36944245D0,
     +         1891356973D0,1897412292D0, 754680739D0,1971204812D0,
     +         1888847798D0,1571641634D0,1117435554D0, 569170662D0,
     +          927407259D0,1490690267D0, 235716977D0, 149289625D0,
     +         1660576129D0,1517266187D0,1229881012D0, 707656279D0,
     +         1869085734D0, 995560464D0, 539146268D0,1604187179D0,
     +         2082150220D0, 370594724D0,2044924591D0, 916100787D0,
     +         1037414126D0,1838122410D0,1265438464D0,1007804709D0,
     +         1257431879D0,2061749697D0, 737009774D0, 408432740D0,
     +          876389446D0,1294711786D0, 965146404D0, 737154017D0,
     +          764970606D0,1074109599D0,1039219247D0, 428641844D0,
     +         1522856686D0,1019054714D0, 805874727D0,1165699491D0,
     +          258880375D0,1554283637D0,1155862579D0, 848396760D0,
     +          915892507D0, 614779685D0, 391842496D0, 380006810D0,
     +         2011769251D0,1860139263D0,1920597088D0,1993412958D0,
     +          511806823D0, 979167897D0,1956806422D0,1256909708D0,
     +          581488682D0, 334258581D0,  68580478D0, 534897944D0,
     +          251676340D0,1051072528D0,2101655234D0,1413698051D0,
     +          796322341D0, 698108846D0,1544249456D0, 857010188D0,
     +         1860488201D0, 355389105D0,1774722449D0,1582405117D0,
     +          553469741D0,1411007767D0,1230102545D0, 356267478D0,
     +          778084663D0,1905014417D0,1109871330D0,1704318220D0,
     +          270593738D0, 483389111D0, 323128013D0, 361076890D0/
      DATA SEED/SBYM*1.0/
      DATA S/0/
      DATA M/0/
      END
```

TABLE I-1: INITIALIZATION SEEDS USED TO GENERATE RANDOM NORMAL DEVIATES FOR 20 CROSS-SAMPLES IN DESIGN A (XX1-XX20)

Cross-Sample	Initialization Seed
XX1	2102089753
XX2	1396324989
XX3	594201671
XX4	1049251362
XX5	195748861
XX6	2143136572
XX7	160875454
XX8	851439770
XX9	126617071
XX10	1318897636
XX11	514694161
XX12	1410932621
XX13	603731346
XX14	1410147358
XX15	706848193
XX16	340061464
XX17	1218029222
XX18	1037466748
XX19	983209347
XX20	2067888841